The impact of business accelerators and incubators in the UK

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THE IMPACT OF BUSINESS ACCELERATORS AND INCUBATORS IN THE UK

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Executive Summary

The number of business incubators and accelerators in the UK has grown rapidly over the last few years. This growth has been facilitated by public funding; in this study we estimate that between £20-30 million of public funding (UK and EU) is being spent on UK incubators and accelerators per year. Despite this, relatively little robust evidence exists regarding their impact.

In this study we explore how incubators and accelerators impact the startups they support and investigate which types of support (e.g. provision of workspace, mentoring, funding or training) drive this impact. We also examine how incubators and accelerators may impact the wider business ecosystems in which they belong.

Most startups consider the contribution of the incubator or accelerator they attended to have been significant or even vital to their success

Through a survey of 428 startups that have previously or are currently attending (i.e. received some combination of support from) an incubator or accelerator, we find that most startups consider the contribution of the incubator or accelerator as significant or vital to their success. Those that attended an incubator are slightly more likely (73%) to report attendance as being significant or vital to their success than those that attended an accelerator (64%).

Accelerator participation is positively associated with startup survival, employee growth, and funds raised

Incubators and accelerators are often selective, only taking on the best startups which apply; this makes it difficult to determine their additionality. To disambiguate this selection effect, we use a regression discontinuity design (RDD) to analyse data from one notable corporate accelerator. We compare outcomes of startups that, on application, scored just above and just below the threshold for being interviewed to compete for a spot on the programme. We find that attending this accelerator is positively associated with three outcomes measures: survival (measured by continued online presence), employee growth, and funds raised.

Most types of support offered by incubators and accelerators are positively associated with at least one outcome measure, but few interventions can be positively linked with multiple outcomes

Our survey of startups reveals that startups perceived direct funding to be the most useful support they received as part of their incubator or accelerator programme. This was followed by access to office space, lab space and technical equipment.

We also use a series of regression models to test the effect of receiving different types of support on the following outcome measures: the startup's overall perception of the impact of attending the programme, growth in employees since attending, change in proportion of employees that hold a degree, change in development stage, innovativeness (as perceived by startup), number of patent applications, R&D expenditure and investment raised.

We find that whilst most types of support have a significant positive association with at least one of the outcome measures above, there was little consistency across the measures. We find strongest evidence that the following types of support may have a positive impact: access to investors, access to peers, help with team formation, direct funding from the programme, press or media exposure, mentoring from an industry expert, help measuring social impact, mentoring from a venture capitalist (VC) / angel. All of these are significantly related to two or more of the outcome measures described above.

While some types of support offered by incubators and accelerators appear to have a direct impact on startup outcomes, others seem to be mediated by changes in startup behaviour

Using further regression models, we explore how the changes that startups make as a result of receiving different types of support may lead to positive outcomes. We find that while some support types (e.g. access to peers and coaching/personal development) appear to act directly on improving startup outcomes, others seem to work through changing how startups approach raising finance, strategic planning, developing and recruiting staff and partnering with external organisations.

Accelerators have positive spillover effects on the wider business ecosystem

In order to understand how accelerators may have a positive impact on the wider business ecosystem in which they belong, we draw on a commercial dataset to analyse how the launch of an accelerator affects the amount of investment going to non-accelerated startups in that region. We exploit the staggered formation of accelerators across boroughs in the UK (excluding London) and the focus of these programmes on accelerating high-tech firms. We find that the launch of an accelerator is associated with a significant increase in the number and value of investments made by VCs into non-accelerated seed and high-tech companies, relative to non-accelerated seed but non-high-tech firms.

Based on insights from our research we present a number of recommendations for what public funders, programmes and local enterprise partnerships can do to support the sector:

For public funders:

Invest in pilot programmes and further research to understand good practice, displacement effects and the longevity of impact incubators and accelerators have.

Continue to investigate other types of intervention (e.g. tax credits, direct grants and network building) alongside incubators and accelerators.

Make data-sharing obligatory for incubators and accelerators receiving public funding.

For incubators and accelerators:

Assess your own impact or share data with researchers to do it for you and use data-driven insights to optimise your programme design.

For Local Enterprise Partnerships:

Understand how incubators and accelerators can be part of your Local Industrial Strategy and connect with other LEPs in order to share experiences and best practices when working with incubators and accelerators.

1. Introduction

1.1 Aims of this report

This report follows a previous study, Business incubators and accelerators: the national picture, which was produced by Nesta for BEIS in April 2017 (Bone et al. 2017). This earlier study described the landscape of accelerators and incubators in the UK, including information about their geographical and sectoral distribution, as well as sources of funding. However, questions about the effectiveness of UK accelerators and incubators on the startups they support, as well as their impact on the wider business ecosystem, were outside the scope of that study. These questions are of significant importance to policymakers, however, especially given the insights from the previous report that the number of accelerators and incubators continues to grow rapidly – and that this growth is being enabled largely by public funding. Based on data collected for this study, we estimate that between £20-30 million of public funding (UK and EU) is currently being spent on accelerators and incubators in the UK per year.[1] Assessing the impact of such programmes is thus of crucial importance in deciding whether this is a cost-effective means of supporting new ventures.

This report will therefore:

Explore previous literature on the impact of accelerators and incubators, both on the startups they support and on the broader business ecosystem;

Produce new evidence concerning the impact that accelerators have on the startups they support, by comparing the outcomes of participating versus unsuccessful applicants to a notable corporate accelerator;

Examine the key objectives of UK accelerators and incubators, and what barriers they face in reaching these objectives, through a survey of nearly 100 UK accelerators and incubators;

Determine which types of support offered by incubators and accelerators (e.g. provision of workspace, mentoring, funding or training) add the most value to participating startups, by analysing the effect of the different types of support received on the outcomes of participants of 109 accelerators and incubators;

Produce a 'theory of change' which explains how these types of support make their impact, based on a quantitative analysis which draws on responses from a survey of 441 accelerator and incubator participants;

Explore what effect UK incubators and accelerators have on their broader business ecosystem, by analysing the effect that a new programme being launched in a region has on venture capital being raised by non-accelerated startups in that region.

[1] Using data collected from this study's survey of accelerator and incubator managers, we estimated the average amount of public funding received by publicly-funded programmes by multiplying each programme's reported annual costs (after removing outliers) by the percentage of their funding mix which they reported as coming from public funding. This gives an estimated average government contribution of £187,150. We then estimated the total amount spent by public funders per year in the UK by extrapolating this to all accelerators and incubators in the 2017 directory (see Bone, Allen, and Haley 2017) which reported receiving public funding (n = 141). This gives an estimated total government expenditure on incubators and accelerators of £26.4 million. To take into account the large margin of error in this calculation we estimate that the true number is somewhere between £20-30m

Investigate how Local Enterprise Partnerships (LEPs) and Growth Hubs interact with or support accelerators and incubators in their region, and how these interactions help both parties reach their objectives, through interviews with 22 LEPs.

We hope that this study will be of interest to policymakers who are involved in stimulating innovation and entrepreneurship and are interested in improving their understanding of forms of startup support. We believe this report will also be of use to incubator and accelerator managers who are interested in how they can improve the cost-effectiveness of the support package they offer, or who wish to measure and better report (to current or potential funders, say) their programme's own impact in the future.

The study was commissioned by BEIS and prepared by authors from the innovation foundation Nesta in collaboration with the London School of Economics, The Open University and commercial startup data provider Beauhurst. Errors and omissions are the responsibility of the authors alone.

1.2 What are business incubators and accelerators?

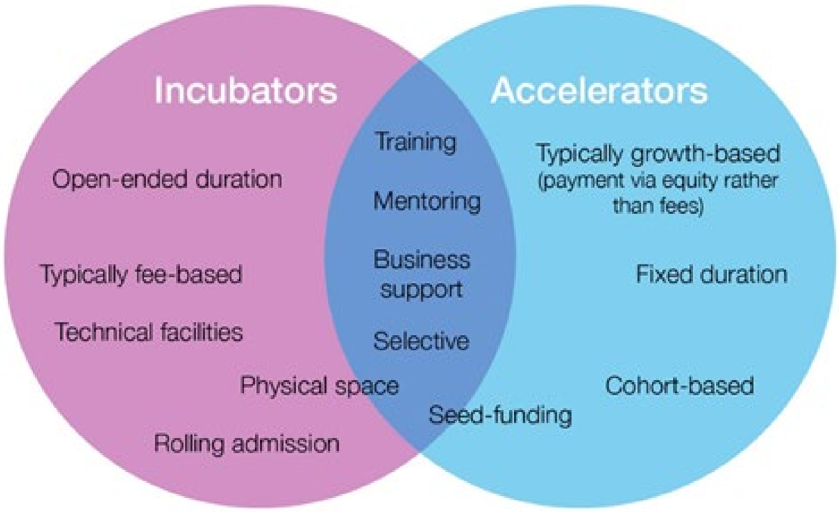
Accelerators and incubators share the common goal of supporting startups through the early and fragile stages of growth. This support can – in theory – help firms avoid the mistakes of others, access funding quicker, grow faster and increase their chances of survival. In this way they both fall under the broader concept of "business incubation" - an umbrella term for a range of support activities, provided by a variety of organisations, not just as the services provided by a self–identified 'incubator' (Dee et al. 2015).

Bone et al. (2017) identified that at the time of data collection (November 2016 - March 2017) there were 205 incubators[2] and 163 accelerators in the UK, as well as some slight variations on these themes in the form of 11 pre-accelerators, 7 virtual accelerators and 4 virtual incubators. However, at the time of that study, the number of programmes was still growing and so we would estimate that the total would likely be larger today.

We follow Bone et al. (2017) in our definitions of incubators and accelerators (Figure 1) and will recap briefly what the similarities and differences are between them and highlight some key facts and figures about the support they offer, their funding models, and their sectoral and geographic distribution. Throughout this report, for ease of readability, we will collectively refer to incubators and accelerators as 'programmes', even though incubators are not strictly programme-based in the same way as accelerators.

[2] This number includes three University Enterprise Zones (UEZ): The Ingenuity Lab in Nottingham, Future Space in Bristol and Digital Health Enterprise Zone in Bradford. These UEZs are a wider concept than that of an incubator, representing specific geographical areas where universities and business work together to increase local growth and innovation. Each UEZ will be supported by a partnership between a university, Local Enterprise Partnerships (LEPs) and others. They have been included because parts of the UEZs share the characteristics we associate with incubators.

Figure 1: Defining Characteristics of Incubators and Accelerators T



Source: (Bone et al. 2017) adapted from (Dempwolf, Auer, and Fabiani 2014)

1.2.1 Incubators

Incubators are not a recent phenomenon: the oldest incubator in the UK is St John's Innovation Centre in Cambridge, which launched in 1987. They are primarily physical workspaces – most studies, such as (CSES 2002) see the provision of physical space as central to the incubator model – with the addition of some shared facilities and business support services, such as mentoring, training and access to investors. Incubators typically provide their services on relatively flexible terms, taking on new businesses on an ad-hoc basis (i.e. they are not cohort-based) for an open-ended duration (on average around two years; Bone et al. 2017).

The majority of incubators are at least partly self-funded through the membership fees or rent they charge their residents. However, they are often also subsidised by a university or public funding (Bone et al. 2017).[3] The relationship between incubators and universities often goes beyond just funding, many being directly managed by a university and supporting spin-outs along with other local businesses.[4] By charging rent, rather than taking equity in the businesses they support, incubators are able to support businesses that are unlikely to scale rapidly and thus, while often having certain eligibility criteria, they are typically less competitive than accelerator programmes.

Incubators in the UK support an estimated 6,900 businesses at any one time. While the majority do not have any specific sectoral focus or broadly cater to digital technology businesses, those that are sector-specific typically focus on life sciences and other science-based sectors such as engineering, healthcare or renewable energy.[5] Incubators are relatively evenly distributed around the UK, often in university campuses or out-of-town science and business parks (Bone et al. 2017; see Figure 2).

[3] 72% of incubators reported being at least partly funded by membership fees / rent, 43% by public money and 34% by a university.
[4] An analysis of the BEIS UK incubator and accelerator directory shows that 99 incubators mention a university either in their programme name or as their organisation name, suggesting that they are university managed.
[5] 45% of incubators reported having no sectoral focus, 29% having a non-specific focus on digital technologies, 26% a focus Life Sciences, 14% on engineering and manufacturing, 13% on Health and wellbeing and 11% on Energy and the Environment.

1.2.2 Accelerators

Accelerators are a more recent phenomenon than incubators, their origins often being traced back to the US programme Y Combinator, which was established in 2005. A few years later[6], accelerators began to appear in the UK and their number has grown rapidly since – driven initially by venture capital, and more recently by corporate funding.

Accelerators, unlike incubators, offer their services through an intensive cohort-based programme of limited duration (usually 3-12 months)[7] and typically focus on services over physical space (Bone et al. 2017).[8] They periodically take in cohorts of startups via a highly competitive process, which is in principle open to all applicants (Clarysse et al. 2015)

Whilst relatively rare in incubators,[9] six out of ten accelerators offer direct funding into participating startups. The majority make investment in return for equity, but some offer other funding such as grants, debt or convertible notes (Bone et al. 2017).

Because accelerators often base their business model on equity from the startups they support, they are more growth-driven; this means that they are typically more selective than incubators, only accepting startups which they think have high growth potential and aiming for these companies to scale rapidly or fail fast, thus minimising wasted resources.

While early accelerator programmes were primarily funded by venture capitalists seeking to deal-flow, this is now relatively rare; instead, the majority of accelerators are now funded by either corporates or the public sector.[10] The high level of corporate interest (and funding) into accelerators is a relatively recent phenomenon and may be one of the key factors which has driven the rapid growth of such programmes in recent years.

An estimated 3,660 new businesses per year are supported by accelerators in the UK. As with incubators, the majority of UK accelerators are cross-sectoral. Where there is a specific focus, this is often based around on a digital trend such as Fintech, Agritech, Edtech, Cybersecurity or Smart cities.

Accelerators are particularly concentrated in the capital, with more than half of UK accelerators based in London. However, as the number of accelerators has grown, an increasing proportion are basing themselves in other startup clusters such as Birmingham, Bristol, Cambridge and Manchester (Figure 2).

1.2.3 Variations

Whilst we have presented incubators and accelerators as distinct archetypes, there is much hybridisation and variation. One noteworthy variation is the online ‘virtual’ incubator or accelerator[11], which offers similar support to its physical counterpart, but without the provision of work, office or laboratory space, and with services such as mentoring and access to networks being provided online. Another significant variant on the accelerator model is the

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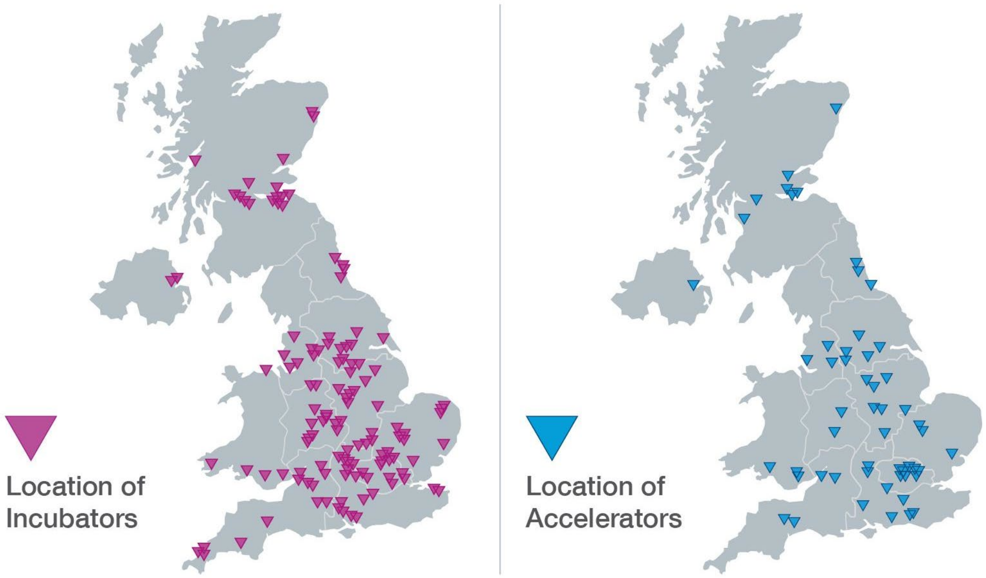
[6] Seedcamp launched in London in 2007, making it the oldest UK accelerator which is currently active.
[7] The average size of a cohort was 16 businesses and the average length of a programme was just over 6 months (27 weeks).
[8] While (by definition) 100% of incubators offer office / work space, it was only reported to be offered by 54% of accelerators.
[9] Direct funding is offered by only 14% of incubators.
[10] Dedicated venture capital firms only fund around 8% of UK accelerators, while corporates fund 51% and public funders 41%.
[11] Virtual accelerators offer support through a fixed term, cohort based programme, whereas virtual incubators, like standard incubators, are more flexible in how and when support is offered.

'pre-accelerator', which provides very early-stage support, lasting from a day to a month, to entrepreneurs who aim to join an accelerator programme in the future.

Alongside these models are an array of other forms of business incubation which offer similar types of support. These include 'startup studios' which aim to generate multiple, parallel ideas in-house before spinning them out,[12] as well as a trend for coworking spaces and venture capital funds starting to provide services more traditionally associated with incubators and accelerators such as workspace and mentoring.[13]

Figure 2: Map of Incubators and Accelerators in the UK



Source: (Bone et al. 2017) adapted from (Dempwolf, Auer, and Fabiani 2014). Please note that in areas of high programme density, triangles may overlap meaning that individual incubators and accelerators are not distinguishable.

[12] See http://www.nesta.org.uk/blog/startup-studios-better-model-build-startups-1
[13] Also see Deep Science Ventures, another programme which challenges our definitions by aiming to bring together 'founder-type' scientists to create and scale ventures.

2. Prior evidence on the impact of incubators and accelerators

Researchers have been trying to assess the impact of business incubators and accelerators for nearly as long as the models have existed. However, previous work is fragmented in terms of the comparisons made, their methodological approaches and the outcome measures used.

Below we present a review of the past literature on the impact of incubators and accelerators on the overall outcomes of participating startups, the effect of programme design, as well as the impact on the wider business ecosystem.

Note that this report does not attempt to be a systematic review of the entire literature on accelerators and incubators; for such an overview, we direct the reader towards (What Works Centre for Local Economic Growth 2017a, [b] 2017; Hackett and Dilts 2004; Mian et al. 2016; Hausberg and Korreck 2018). Table 1 gives a summary of the literature reviewed.[14] For an extended literature review see Appendix 5.1.

2.1 Impact on overall outcomes of participating startups

One of the major challenges in conducting research into the impact of incubators or accelerators is that there rarely is one single measure of success. Many programmes are themselves unclear whether their primary motivation is to improve firm survival, create wealth or create jobs. This issue has been apparent for some time (see. Phan et al. 2005; Van Hove et al. 2015), and clearly complicates analysis.

A second challenge is the fact that many programmes, especially accelerators, typically are highly selective – that is, they aim to take only the highest quality startups. As a result, we would expect 'graduates' of selective programmes to be more successful than non-participating firms, regardless of whether or not the programme itself contributes to this success. A further complication results from the possibility that if the very best quality startups decide they do not require external support and thus do not apply to programmes, then self-selection by startups may bias findings in the opposite direction, resulting in the underestimation of programme impact. Research that does not take these selection bias into account risks incorrectly estimating the effect of a programme.

A related issue is the signalling effect: since many programmes are not only highly selective but are known to be so, participation may be perceived as a mark of quality which, in itself, impacts a firm's subsequent opportunities. For example, since YCombinator is known as producing high quality firms, 'graduates' will find it easier to gain the attention of investors.[15] Unlike the selection effect, this signalling effect is a genuine contribution towards success by

[14] The earliest studies that explored the impact of the fluid field of startup support, looked at the impact of being located on a Science Parks (e.g. (Westhead 1997)). A review of the literature on science parks concluded that the returns to being located in a science park seem negligible (Siegel, Westhead, and Wright 2003). They speculate that imprecise estimates may be due to differences in the types of science parks, their ownership and the types of services provided to firms.

[15] In a similar way, the signalling value of educational degrees is hotly debated by economists, in a field pioneered by Nobel Laureate Michael Spence.

the programme – but is more a function of the programme's past performance (including its ability to select) than the support directly provided to current firms.

Several studies have tried to assess the overall impact accelerators and incubators have on the startups they support. While some studies make little or no attempt to take into account the selectivity of programmes (Christiansen 2014; Rothaermel and Thursby 2005a, [b] 2005; Roberts et al. 2016; Department for Business, Energy and Industrial Strategy 2019; Amezcua et al. 2013; Amezcua 2010),[16] others and have used various methods to try and control for the selection bias mentioned above.

One method that has been used to test the effect of incubators is to analyse the effect the amount of time spent in an incubator has on outcomes for firms (Rothaermel and Thursby 2005a, [b] 2005). While only looking at participating startups removes the issue of programme selectivity, because it does not allow comparisons with startups that did not attend a programme at all, conclusions about overall impact that can be drawn from such analyses are limited.

The most common method of analysing the impact of incubators and accelerators is to compare participating startups to a matched control group of similar firms (Colombo and Delmastro 2002; Schwartz 2009; Yu 2016; Smith and Hannigan 2015; Hallen et al. 2014; Lasrado et al. 2016). However, it is not clear whether the characteristics used to conduct this matching adequately represent those that contribute to firm success in the selection process. Colombo and Delmastro (2002b), for example, use firms' location, industry, age, and legal form to perform matching of firms but later find evidence that incubators attract firms with better-than-average human capital, which they do not control for.

A potentially more robust method used is to compare the outcomes of participating startups with those that applied to but were narrowly rejected from a programme (Hallen et al. 2016). Better still, Gonzalez-Uribe and Leatherbee (2016) and Fehder (2015) robustly take into account the selectivity of the accelerator they study by controlling for differences in quality among applicants using the numerical scores given to firms by judges when applying to the accelerator (using what is known as a regression discontinuity design, RDD; Thistlethwaite and Campbell 1960).

Bringing together evidence from studies using these different methodologies, there is some moderately strong evidence that incubators can increase the rate at which participating firms grow in employee size (Colombo and Delmastro 2002; Lasrado et al. 2016; Department for Business, Energy and Industrial Strategy 2019). However, evidence for incubators' effect on survival rates is mixed, with one study finding that incubators increase survival (Rothaermel and Thursby 2005b) and another suggesting that they decrease survival rates (Schwartz 2009). While decreasing survival rates may appear to suggest that these incubators have a negative impact on the startups they support, this may not necessarily be the case. Rather, it may indicate that incubators can help firms understand the viability (or unviability) of their idea, resulting in them killing bad business ideas sooner than they otherwise would; and thus preventing time and money being wasted on businesses that were doomed from the get-go. Furthermore, Rothaermel and Thursby (2005a) find that firms that remain longer within an incubator may be less likely to raise VC funds but more likely to generate significantly higher

[16] For example, by simply comparing participating startups to those that applied but were not accepted e.g. Roberts et al. (2016), comparing outcomes of startups moving to an incubator with those moving to another property (Department for Business, Energy and Industrial Strategy 2019), comparing outcomes of startups which have participated in incubators and accelerators with different attributes (Amezcua et al. 2013; Amezcua 2010), surveying perceived impact of participating startups (Christiansen 2014) or analysing the effect the amount of time spent in an incubator (Rothaermel and Thursby 2005a, [b] 2005).

revenues. This illustrates some of the tensions that are apparent, and the need to define success criteria before one can determine performance.

Evidence for the impact of accelerators is slightly stronger. We have moderately strong evidence that accelerators can increase the speed at which startups raise investment (Roberts et al. 2016; Hallen et al. 2016; Fehder 2015; Hallen et al. 2014), gain customer traction (Hallen et al. 2016, 2014), grow their number of employees (Gonzalez-Uribe and Leatherbee 2016; González-Uribe and Reyes 2019; Lasrado et al. 2016; Fehder 2015), and reduce the time it takes them to be acquired (Hallen et al. 2016; Smith and Hannigan 2015). We also have some weaker evidence that accelerators may increase the rate at which firms grow their revenues (Lasrado et al. 2016; Roberts et al. 2016). Furthermore, as with incubators, accelerators may help funders to understand the viability of their business idea and thus, help bad ideas to 'fail faster' (Smith and Hannigan 2015; Yu 2016).

To further complicate the picture, while Lasarado et al. (2016) shows that university affiliated programmes are associated with faster sales and job growth than those not connected to a university, another study by Amezcua (2010), finds that while university affiliation has a positive effect on firm survival, it has no effect on employment or revenue growth of participating firms.

While the studies above give us some indication of the impact of incubators and accelerators on the startups they support, they are far from conclusive – and leave unanswered questions about how these findings can be transposed from overseas into the UK context. Alongside this, only a few – such as (Gonzalez-Uribe and Leatherbee 2016; González-Uribe and Reyes 2019; Fehder 2015) – satisfactorily control for the selectivity of programmes.

2.2 The effect of programme design on impact

Many of the studies described above treat programmes as 'black boxes'. However, several studies have attempted to look inside these boxes in order to understand what types of support offered by incubators and accelerators add the most value to participating startups. Once again, evidence on this question is weaker for incubators than for accelerators.

The type of support offered by incubators and accelerators appears to be important to the impact of programmes. There is moderately strong evidence that providing networking opportunities (Amezcua et al. 2013; Hallen et al. 2016; Christiansen 2014; Roberts et al. 2016) and mentoring (Hallen et al. 2016; Gonzalez-Uribe and Leatherbee 2016; Christiansen 2014) are important to the success of incubators and accelerators. We also have some weak evidence that management training may be beneficial (Amezcua et al. 2013). However, the impact of other forms of support (e.g. office space, direct funding, and demo days) is less clear.

2.3 The effect of incubators and accelerators on the broader business ecosystem

It is of interest to policymakers not only what impact incubators and accelerators have on the startups they support, but also what spillovers they may create – that is to say, whether (and how) such programmes may affect the startup ecosystem more generally. The stronger such spillover effects, the greater the argument for public support of such programmes.

We have some evidence that incubators may promote the creation of high-quality jobs in their region (Department for Business, Energy and Industrial Strategy 2019) and that accelerators may bring an increase in VC funding going to non-accelerated firms as well to those which do participate (Hochberg and Fehder 2015). The latter study however, is focussed on the US and it is not clear how this will translate to the UK context.

Table 1: Summary of literature review

Study	Focus	Conclusions	Method	Country of programme(s)
Rothaermel and Thursby (2005b)	Incubators	Incubators may protect firms from failure during residence, but not increase post-graduation. This effect is stronger for university affiliated, than non-university affiliated, incubators.	Analyses what effect the amount of time spent in incubators has on failure / graduation rates	US
Rothaermel and Thursby (2005a)	Incubators	Firms that remain longer within an incubator may be less likely to raise VC funds but more likely to generate significantly higher revenues	Analyses what effect the amount of time spent in incubators has on failure / graduation rates	US
Hallen et al. (2016)	Accelerators	Positive effect on survival by some, but not all, early accelerators	Compares accelerator participants to those almost accepted onto the same cohorts	US
Fehder and Hochberg (2014)	Accelerators	Launch of an accelerator was associated with an increase in the number of VC deals and the total amount invested in the region	Compares changes in regions following launch of an accelerator with similar regions that do not have one	US
Smith and Hannigan (2015)	Accelerators	Positive impact of ‘top’ accelerators on speed of exit (acquisition or quitting); negative impact	Compares outcomes of accelerated startups to matched group of non-	US

Study	Focus	Conclusions	Method	Country of programme(s)
		on speed of follow-on funding.	accelerated startups	
Yu (2016)	Accelerators	Negative impact on funds raised and survival (though possibly deliberate)	Compares outcomes of accelerated startups to matched group of non-accelerated startups	US
Hallen et al. (2014)	Accelerators	Positive effect on VC raised, and on customer traction by some, but not all, accelerators	Compares outcomes of accelerated startups to matched group of non-accelerated startups	US
Roberts et al. (2016)	Accelerators	Accelerated firms had higher revenue growth and investment growth, but no effect on employee growth. Networking opportunities and access to funding (direct and indirect) were perceived to be the most useful types of support by participating	Compares outcomes of accelerator participants to startups that applied, but were not accepted onto a programme	Worldwide
Colombo and Delmastro (2002a)	Incubators	Positive impact on employee growth; no effect on R&D intensity	Compares outcomes of incubated startups to matched group of non-incubated startups	Italy
Schwartz (2013)	Incubators	Negative effect on survival (though possibly deliberate)	Compares outcomes of incubated startups to matched group of non-incubated startups	Germany

Study	Focus	Conclusions	Method	Country of programme(s)
Lasrado et al. (2016)	Incubators and accelerator	Positive effect on growth (of revenue and employees) for incubators and accelerators. University affiliation incubation is associated with growth than non-university incubation.	Compares outcomes of incubated startups to matched group of non-incubated startups	US
Department for Business, Energy and Industrial Strategy (2019)	Incubators and accelerator	Positive effect of incubators on growth of participating startups (turnover, employees and productivity) with no observed displacement effect for the surrounding area. Also, increased high-quality jobs in area surrounding incubator site.	Compares outcomes of startups moving to an incubator with those moving to another property. Also tests impact of moving to a property located in area surrounding an incubator site.	United Kingdom
Amezcua (2010)	Incubators and accelerators	University affiliation has a positive effect on firm survival	Compares outcomes of startups which have participated in different incubators and accelerators	US
Amezcua et al. (2013)	Incubators and accelerators	For firms operating in a competitive business environment, participating in an incubator or accelerator that offers networking and management training produces firms with higher survival rates	Compares outcomes of startups which have participated in different incubators and accelerators	US
González-Uribe and Reyes (2019)	Accelerators	Positive impact of entrepreneurship schooling (i.e., no funding) on sales, employment and profits. The impact is	Instrumental variables exploiting random allocation of applicants to evaluators with	Colombia

Study	Focus	Conclusions	Method	Country of programme(s)
		concentrated on high-growth startups.	different scoring generosities.	
Gonzalez-Uribe and Leatherbee (2016)	Accelerators	Positive impact of entrepreneurship schooling bundled with basic services on employment. No evidence that basic services of funding and coworking space affect performance on their own.	Regression Discontinuity Design	Chile
Fehder (2015)	Accelerators	Positive effect on both employment and funds raised	Regression Discontinuity Design	US
Christiansen (2014)	Accelerators	Most participating startups believe that accelerators are adding value in excess of the funding they give	Surveys participating startups about what they perceive the impact of the accelerator they attended to be	Worldwide

3. New Research

3.1 What are the goals and objectives of incubators and accelerators?

3.1.1 Methods

Focus group discussions

We held four focus group events at Nesta in December 2017 and January 2018. The primary aims of these focus groups was to better understand the goal-setting processes of incubators and accelerators and the feasibility of our research approach, as well as to gain further insights into the best way to ask questions and the response options we should give in the subsequent surveys. Separate events were held for accelerator managers, incubator managers, accelerator attendees and incubator attendees.[17] Incubators, accelerators and participating startups were chosen such to try and represent different geographies, sectors and funding models as best as possible. The topic guides and agenda for these focus groups are listed in Appendix 5.2.

Survey of accelerators and incubators

Between February and March 2018, we surveyed accelerators and incubators in order to gain insights into what objectives were most important to their programmes; what they perceive as their programme's biggest benefits for participating startups (see Section 3.42 for results) and what they saw as their main barriers to more impact (see Section 3.82 for results). The survey was disseminated to all incubators and accelerators in the online directory which was produced by Nesta for BEIS in April 2017.[18] In total, 99 programmes (61 incubators and 38 accelerators) completed the survey, which represents more than 25% of the overall pool of 368 programmes in the UK. The incubators and accelerators surveyed are slightly larger, on average, than the national average[19] and are reasonably representative with regard to geographical distribution.[20] Compared to the national average, our survey sample contains considerably more incubators and accelerators with a specific sectoral focus (e.g. Education, Fintech or Agritech) than the national population.[21]

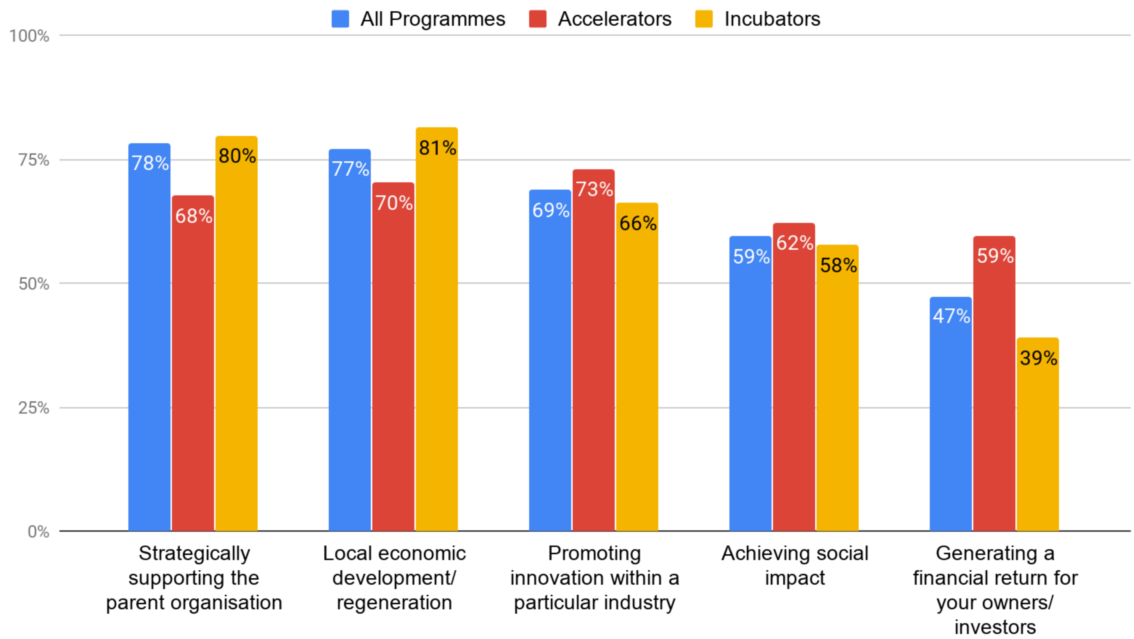
[17] N = 7,8,7,5, respectively.
[18] The online directory (thought to be comprehensive at time of publication in 2017) is available at: https://www.gov.uk/government/publications/business-incubators-and-accelerators-the-national-picture
[19] On average the accelerators surveyed take on 25 new business a year (national average = 22) and the incubators take on 54 new businesses a year (national average = 34). National averages are according to Bone et al. 2017.
[20] Some exceptions to this are that our sample contains no accelerators in the North East (national percentage = 3%), East Midlands (national percentage = 5%), South East (national percentage = 6%) or Wales (national percentage = 2%) and no incubators in Wales (national percentage = 3%) or Northern Ireland (national percentage = 1.45%). Our sample also contains a considerably lower percentage of accelerators in the West Midlands (3%) than the national average (7%) and a considerably higher percentage of incubators in London (38%) than the national average (14%).
[21] 21% of incubators and 20% of accelerators in this sample reported not having a sectoral focus, compared to a national average of 45% and 30% respectively (Bone et al. 2017).

3.1.2 Results

The key objectives of both incubators and accelerators are strategically supporting their parent organisation, local economic development / regeneration and promoting innovation within a particular industry.

There was not a single objective that stood out as being considerably more important than the others. All five options offered to accelerators and incubators are seen to be important or very important to more than half of the programmes surveyed (Figure 3). But, for both incubators and accelerators the most important objectives are: strategically supporting their parent organisation or local economic development / regeneration or promoting innovation within a particular industry. Following closely behind in importance is achieving social impact and generating a financial return for owners / investors.

Figure 3: Proportion of programmes that deemed each objective as 'Important' or 'Very Important'



Total programmes = 96. Accelerators = 37. Incubators = 59.

What exactly is meant by ‘strategically supporting the parent organisation’ depends on the nature of that programme. For example, for those run by a corporate, this may mean promoting an entrepreneurial culture internally or finding solutions to specific problems the corporate is facing, while for those run by a university this may be about spinning out innovations developed from university research or developing the skills of its students and staff.

In general, there is little difference in what accelerators and incubators reported their objectives to be. It is, however, worth noting that accelerators are more likely to regard generating a financial return for investors as a key objective. This may be due to the fact that accelerators in this sample are nearly two times as likely to be funded by private investment than incubators.

Incubators, on the other hand, are slightly more likely to report both strategically supporting the parent organisation and local economic development as being important objectives. The varied objectives of the programmes surveyed indicates that when measuring their impact, it is important to consider not one but several different outcome measures.

3.2 What is the overall impact of programmes: as perceived by participating startups?

3.2.1 Methods

Survey of startups

To understand what startups perceive to be the overall impact of the incubator or accelerator they participated in, we conducted a survey of startups that applied to or participated in one of these programmes. Data from this survey was also used for analyses asking questions about which support types have the most impact on startups (section 3.4) and through which mechanisms does support have impact? (Section 3.5).

Our sampling strategy consisted of two stages between April 2018 and September 2018. In the first stage, we asked all accelerators in Nesta's directory that had programmes in the UK to share our survey with their applicants (or else to share applicants' contact details with us so that we might contact them directly). In the second stage, we contacted startups that were known by Beauhurst[22] to have participated in an accelerator.[23] It is important to note that Beauhurst does not have information on startups that have been through an incubator. As a result, our survey sample was skewed towards startups that had been through an accelerator rather than an incubator.

The total startup sample comprised of 441 enterprises (343 had been through an accelerator, 66 an incubator, 23 another support type with elements of an accelerators or incubator e.g. coworking spaces with additional support services and for 9 the type of programme was unknown), of which 324 had participated in an accelerator or incubator, 104 were currently participating, and 13 applied but did not participate. Due to accelerators being a relatively recent phenomenon, the average startup in our sample joined a programme 2016: 36 startups joined in 2018, 96 in 2017, 89 in 2016, 50 in 2015, 20 in 2014, and 31 in 2013 or earlier. As a result of our sampling approach, we count 109 unique programmes in our sample.[24] See Appendix 5.3 for more information on the sample of startups that responded to this survey.

3.2.2 Results

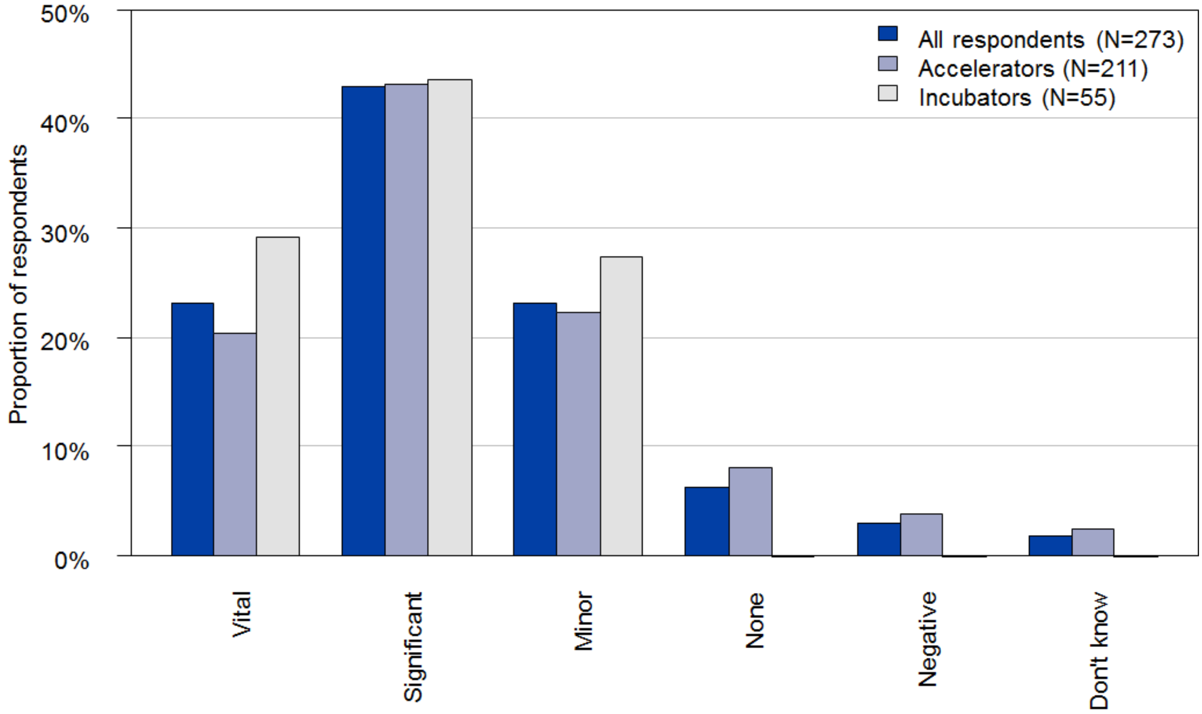
Most startups surveyed consider the contribution of incubators and accelerators they participated in to be significant or even vital to their success.

Of the startups we surveyed 43% report that the accelerator or incubator they participated in was significant to their success and 23% say that it was vital (Figure 4); only 9% of startups find no contribution or a negative impact of their programme on the success of their business.

[22] Beauhurst is a searchable database of the UK's high-growth companies: they track every company raising equity, graduating from an accelerator, receiving an innovation grant, spinning out from a university and more.
[23] At the time of the survey Beauhurst had information on 4,690 startups that had been through an accelerator. Of these they had a contact email address for 3,086, all of which were contacted about the survey.
[24] Defining programmes run by one parent organisation for multiple clients as a single programme. Individual analyses may use fewer observations depending on missing values in the variables considered in each analysis.

Accelerators are perceived to have a vital or significant impact less often (64%) than incubators[25] (73%), but this difference is not statistically significant. This graph shows the proportion of responses to each option for the question “Looking back, what impact has the support provided by [the accelerator or incubator] had on this enterprise’s chance of success?” These proportions closely mirror the findings for companies participating in European incubators (CSES 2002).

Figure 4: Impact of accelerators and incubators.



3.3 What is the overall impact of programmes? An analysis of one corporate accelerator

3.3.1 Methods

Regression Discontinuity Design

We are interested in estimating the impact of a specific accelerator on future venture performance. To explore this question, whilst attempting to disambiguate the selection effects discussed in Section 2.1 above, we follow (Gonzalez-Uribe et al. 2018), using data from the same corporate accelerator studied in that work: an accelerator run by a large US-headquartered technology firm with various locations worldwide, including London. The corporate accelerator in question was launched in 2011 and is a 4-month programme for later-stage startups. It provides no seed capital, and requires no fee or equity stake, but focuses on the provision of four services: 1) Shared office space; 2) Free access to software, developer tools, and cloud services from the corporate sponsor; 3) Workshops and personalised

[25] The majority of these are incubators but it may also include some coworking space and other forms of business support.

guidance; and 4) Access to the corporate sponsor's network beyond 4 months through the alumni network.

As argued in more detail in Gonzalez-Uribe et al. (2018), focusing on this corporate accelerator is useful on two accounts. First, the structure and services provided by the corporate accelerator are standard among business accelerators. Thus, our analysis can be informative about the potential impact of corporate accelerators more generally, rather than exclusively about the accelerator of the corporate sponsor we focus on. Second, and as explained in more detail below, the selection process of the accelerator can be exploited to design an empirical strategy that distinguishes the potential impact of the programme, from the ability of the staff in picking high quality applicants.

The selection process for the participants in each cohort at the accelerator is a four-part process. First, applicants send their applications online through a specialised platform that collates all information for the accelerator. Next, key staff at the accelerator score in groups the applications based on the business idea, the market and the team (scores range from 1 to 5; with a score of 5 [1] indicating a top [bottom] applicant).[26] Given the high demand for the programme, and the fact that the scoring process is made as a group, it takes the staff roughly two days to go over the applications in each cohort: the goal is to cover 60 applications per day. Once the staff reviews all applications, these are then ranked from best to worst based on the group scores. Next, the staff interviews the top 20 applicants: interviews are long and in-depth, and there are constraints to the staff members' time. Ties are resolved with an open discussion until 20 companies (among those ranking in the top 20) are finally chosen. In the final step, the staff picks 5-10 participants, depending on predetermined capacity.

We use data on 638 applicants to 5 cohorts in the London branch of the business accelerator during the 2013-2016 period collected by Gonzalez-Uribe et al. (2018).[27] The data includes information from the applications, including: applicants' scores, participation status (see Appendix 5.4 for sample composition [Table A3] and characteristics of applicants [Table A4]). To measure impacts, we use additional information collected by the authors from various online sources during 2018 — i.e., within five years of application to the programme.[28]

We focus on three main variables to measure applicants' performance.[29] First, Online Presence (a measure of firm survival, as used by Gonzalez-Uribe and Leatherbee (2016), Yu (2016) and Kerr et al. 2014), an indicator variable of whether the company has a profile on LinkedIn and/or Crunchbase (a widely-used business information platform, originally built to track startups).[30] Second, Change in Employees, which uses the employee size reported in

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[26] The five individuals scoring the applications include all the chief officers in the accelerator: chief executive officer, chief marketing officer, chief technology officer, chief operations officer and chief investment officer.
[27] The application dates for the 5 cohorts closed, respectively during November 2013, July 2014, February 2015, September 2015 and January 2016.
[28] The data on the company's LinkedIn profiles was collected during January-April 2018 and the data from the Crunchbase profiles was collected during September-December 2018. Relative to the application dates, these data collection points roughly measure employment (fundraising) outcomes 2 (3) years after application at the minimum, 4 (5) years after application at the maximum and 3 (4) years at the mean.
[29] We also collected information on patents and trademarks by searching for the company names in the United States Patent and Trademark Office patent and trademark files. Less than 5% of the sample firms appeared in these files, so we did not include these variables in the analysis. Potential explanations for the limited overlap include the concentration of our sample firms in sectors where intellectual property is not usually protected with patents.
[30] While online presence is a commonly used measure of firm survival, it is not without caveats. Profiles in Crunchbase and LinkedIn are self-reported and are not unilaterally taken-down by platforms if companies die. Thus, reliance on this measure of survival risks bias if acceleration alters social media behaviour of firms. The direction of this bias, however, is not clear. For example, if acceleration improves social media management of

LinkedIn and compares it to the number of employees reported at the application stage.[31] Because LinkedIn does not report the actual number of employees, but rather classifies firms into 8 buckets of size, the variable Change in Employees can take the value from -8 to 8.[32] There are a few instances (45) in which the company has a profile on Crunchbase, but no profile in LinkedIn. In those situations, we infer the variable Change in Employees using the employee size reported in Crunchbase and its comparison to the number of employees reported at the application stage.[33] Third, Change in Fundraising, which uses information reported in Crunchbase on fundraising from outside investors and compares it to the information on outside fundraising reported at the application stage. We present results using both changes in the levels of fundraising, as well as changes in the logarithms of fundraising.[34] For observations with 0 in the amount of fundraising (at application or post application), we replace the value with the logarithm of the unconditional fundraising mean in the sample.[35] Results are robust to running the log regressions without arbitrary replacements of the zero values.

Our empirical strategy is a fuzzy regression discontinuity approach (RD) that exploits the top-20 interview threshold rule to estimate a local average treatment effect of corporate acceleration on new venture performance. This rule implies that the probability of acceleration changes discontinuously at the interview threshold as a function of the applicant's ranking Therefore, the difference in expected outcomes between the startups in opposite sides of—but sufficiently near—the threshold can provide the basis for an unbiased estimate. For evidence of the discontinuity in the probability of acceleration at the interview threshold see Appendix 5.5.

To control for differences in characteristics across cohorts, such as number of years between the application dates and 2018 (the year we measure performance), we include cohort fixed effects in the estimation. These fixed effects effectively restrict the comparison to applicants on either side of the interview threshold, but within the same cohort.

The main identification assumption is that ranks are not precisely manipulated around the threshold. Because the scoring of applications is done by judges in group form, where views are openly discussed, such manipulation of rankings by applicants or by judges (for example, so as to help a friend qualify) is hard in this context. Other factors mitigating potential manipulation include the facts that the scoring process extends over more than one day, and the fact that backfilling of scores is not permitted (i.e., once assigned, applications scores are final). For evidence against the empirical relevance of potential precise manipulation of ranks around the threshold see Appendix 5.5.

A different empirical concern regards the possibility that the evaluation process does not result in a continuous score function, particularly in the top of the distribution, and which would be

firms, and given that the propensity to have a profile in either platform at application is the same across selected and rejected applicants.

[31] In unreported regressions, we show results are robust to using information on number of employees from Crunchbase.

[32] LinkedIn classifies companies into 8 company size codes: 1-10, 11-50, 51-200, 201-500, 501-1,000, 1,001-5,000, 5,000-10,000 and 10,000+ employees.

[33] Crunchbase classifies companies into 9 company size codes: 1-10, 11-50, 51-100, 101-250, 251-500, 501-1,000, 1,001-5,000, 5,000-10,000 and 10,000+ employees.

[34] Fundraising values are measured in US dollars; we convert any other currencies using historical exchange rates at the time of fundraising and the time of application.

[35] That is, Log Changes in Fundraising=Log Fundraising Post-Log Fundraising Application, where Log Fundraising Post= Log(Fundraising Post+Mean(Fundraising Post)) and Log Fundraising Application= Log(Fundraising Application +Mean(Fundraising Application)); where Mean(Fundraising Post) equals $457,396 USD and Mean(Fundraising Application)=$150,565 USD.

best suited for the RD design. A group-based evaluation process is more likely to lead to ties (i.e., companies with the same score) than evaluations based on average scores from multiple judges that individually score the companies. In practice, the prevalence of ties among top applicants was low, but varied across cohorts (see Appendix 5.5): all cohorts but two ranked less than 26 companies among the top 20 companies.

To address this concern, we split the cohorts into two groups based on the number of applicants ranked among the top-20: bottom 2-quantile and top 2-quantile. Out of the five cohorts, three are classified as bottom 2-quantile: cohort 1 with 22 (out of 41) top-20 ties, cohort 3 with 23 (out of 130) top-20 ties and cohort 4 with 20 (out of 98) companies in the top 20. Cohorts 2 and 5 are classified as top 2-quartile with 25 (out of 168) and 37 (out of 201) top-20 ties, respectively. In the estimation, we allow results to vary by these two groups. Likely because the prevalence of ties was low on average, we find no statistically significant difference in the results across the two groups (see Appendix 5.5).

Under the identification assumptions, any average performance differences between firms ranking closely to but on either side of the threshold can be attributed to the effects of acceleration. Note that any differences are unlikely to be explained by psychological reactions to the evaluation: scores were not revealed to any applicant.

Naturally, it is possible that the accelerator has positive spillover effects, even among the companies that do not participate in the program. For example, the arrival of accelerators has been found to be positively associated with the development of entrepreneurial ecosystems, as measured by venture capital fundraising (see Fehder and Hochberg, 2014; and Section 3.5 below). In that case, the RD estimate will measure the effects of the programme on participants, above and beyond any potential effects of the accelerator on the region. It is however, also possible that if accelerated firms in any way compete with un-accelerated firms (in product or labour markets or in raising external capital), then it is possible that negative spillover effects might occur, leading to effects of the programme being over-estimated

3.3.2 Results

Accelerator participation is positively associated with startup survival, employee growth, and funds raised

Using data from one notable corporate accelerator and utilising a regression discontinuity design to take into account the selection effects discussed previously, we find that attending the accelerator was positively associated with our three outcome variables: survival (as measured by online presence; $p < 0.01$)[36], change in number of employees ($p < 0.01$), and change in fundraising ($p < 0.01$), within five years of application to the programme.

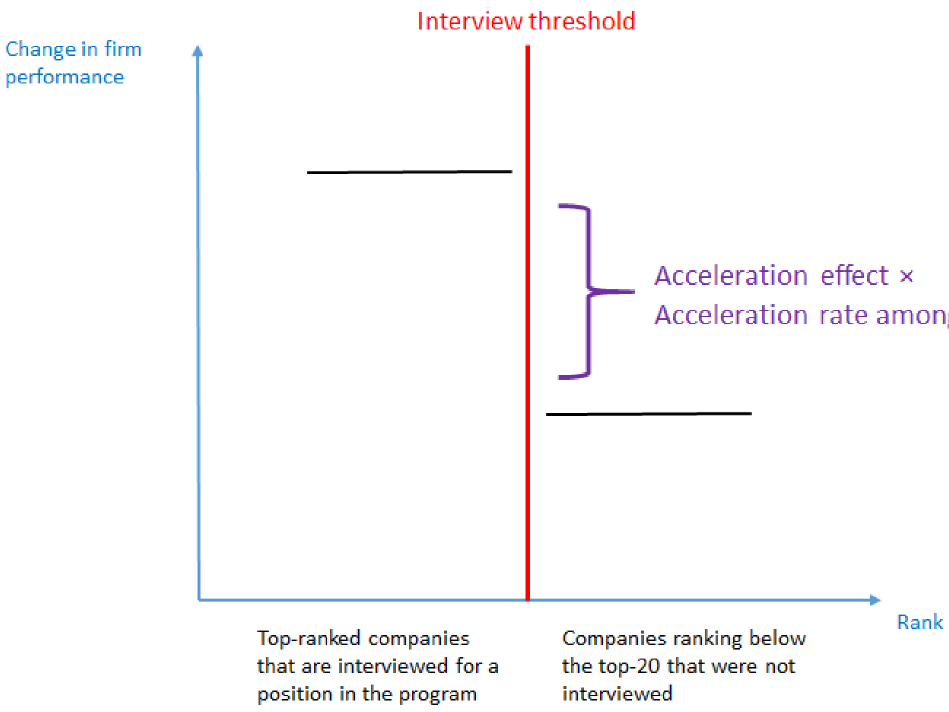
Importantly, this analysis takes into account the fact that the accelerator is selective of the startups that participate by using a regression discontinuity design to compare outcomes of startups just above and just below the threshold for being interviewed for a place on the programme (based on the numerical scores given to startups on application). Figure 5 illustrates this in a simplified way, without using real data. The vertical red line shows the interview threshold, startups scoring below this threshold (to the right of the red line) were not interviewed, those to the right were (on the left). The jump in height (the 'discontinuity')

[36] In statistical hypothesis testing, the p-value, for a given statistical model, is the probability of finding the observed, or more extreme, results when the null hypothesis is true. The null hypothesis is that there is no difference between the populations (or no effect of the treatment) being tested. The p-value is a number between 0 and 1. A small p-value (typically ≤ 0.05) indicates strong evidence against the null hypothesis, so you reject the null hypothesis.

between the two horizontal lines either side of the interview threshold shows the effect on the acceleration probability of being interviewed (the “first stage”), combined with the effect of actually participating in the accelerator on future firm performance. Intuitively, our regression discontinuity approach estimates the acceleration effect as the ratio between the size of the discontinuity and the size of the first stage.

We find that acceleration leads to an increase of 50% in online presence for the applicants at the margin of acceleration. Acceleration also increases employment growth, helping applicants transition up, by roughly one level, in the online classification of employee size. Given that the average applicant has 5 employees at application (i.e., the first level of online employee size: 1-10 employees), the estimated average transition is towards the second level of employee size: between 11 and 50 employees. Finally, acceleration also increases fundraising by 77.6%. Given that the average applicant has raised £115,000 ($150,000 USD, See table A4) at application, the estimated fundraising increase from acceleration amounts to circa £90,000. Results are robust to controlling for differences in fundraising at the application stage, and to using levels or logarithmic transformations to control for outliers. See Appendix 5.6 for a more detailed explanation of the results.

Figure 5: A schematic of the regression discontinuity analysis. Note that this chart is not using real data but is a simplified representation of the analysis.



3.4 Which support types have the most impact on startups?

3.4.1 Methods

With data from the survey of startups we conducted (see Section 3.21 for details), we use a range of regression models to measure the relationship between types of support provided by programmes and outcomes measured at the startup level (obtained through the startups survey). In order to understand which types of support have the greatest impact, we exploit the fact that different programmes offer different combinations of support. This means that we only need to compare outcomes of startups that participated in different programmes (and therefore received different types of support), rather than comparing them to outcomes of startups that did not participate in a programme at all. This means that programme selectivity is less of an issue here and it is not necessary to use a regression discontinuity design (as used in the previous Section). We show definitions of the outcome measures, independent variables of interest and control variables used in our regression models in Appendix 5.7.[37]

Our main models do not distinguish between accelerators, incubators and other programmes for two reasons. The first one is theoretical: the goal of these estimations is to find the types of support that make a difference to startups irrespective of whether the support is offered by an accelerator or incubator. One possible limitation of this approach is that while accelerators and incubators offer similar types of support, the time spans over which support is delivered is typically quite different. For example, the average length of an accelerator programme is six months whereas the average time startups spend in an incubator is around two years. Although we know approximately when startups in our sample joined an accelerator or incubator (e.g. 90% joined since 2013), we do not know how long they took part in the programme for, so our study is unable to determine how the timespan over which different types of support are provided affects the impact it has or for how long this impact lasts.

The second reason is econometric: because support type and mentoring, if modelled correctly, encompass the effects of accelerators and incubators on startups, separate control variables for accelerators and incubators would be collinear with the support and mentoring variables and would destabilise the models. As a robustness test, we re-estimate our main models for the subsample of accelerators.

3.4.2 Results

Access to peers, mentoring, business skills development and coaching are the most common types of support received as part of incubator and accelerator programmes

A large majority of startups that responded to the survey report being provided with access to peers, mentoring and business skills development as part of the accelerator or incubator they participated in. In addition, most startups receive some personal coaching or development alongside typical accelerator services such as office space, help testing and refining their business model or networking opportunities with investors (Figure 6). Many programmes offer access to potential customers and investors, which reflects the conventional picture of

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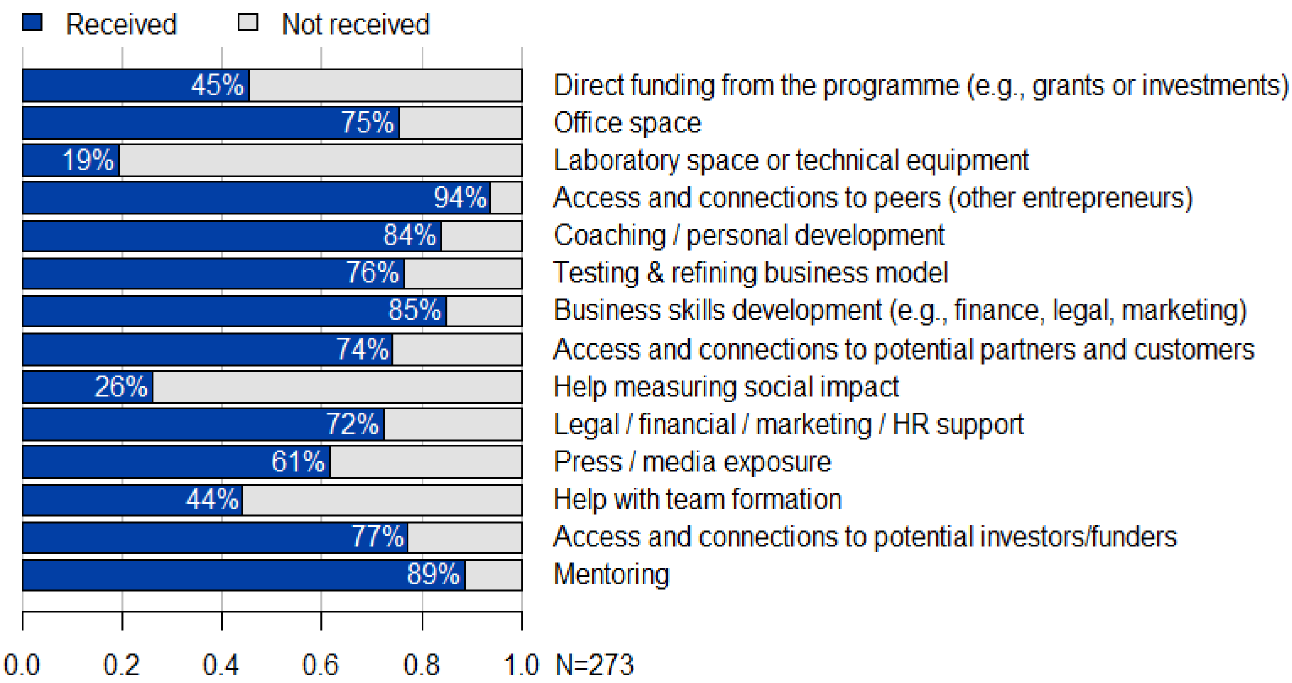
[37] To balance data availability and the level of detail in our results, we run our main regressions with a full set of control variables and a reduced set of variables (see Appendix 5.10). In the latter models, we drop insignificant variables based on their contribution to the model. This has the disadvantage of changing the set of control variables from model to model but can highlight effects may remain hidden in models with too many control variables relative to the number of observations. Changing the set of control variables between models is not necessarily a problem if one believes that not all control variables are related to all outcomes.

accelerators and incubators drawn in the literature. A relatively low observed frequency of laboratory space can be explained by the sector distribution within our sample. Similarly, about a quarter of startups receive help in measuring their social impact, which reflects the substantial proportion of programmes that pursue social and not-for-profit goals.

Figure 6 below shows the proportion of startups that received each type of support. The types of support are ordered by decreasing perceived impact. Not received may refer to both services that are not offered by a programme at all or to services that are offered but that the startup did not make use of.

Figure 6: Types of support received by startups



The relatively low proportion of programmes providing direct funding is more surprising given the emerging understanding of accelerators as cohort-based programmes with a fixed duration that typically provide some equity to startups. Incubators and related programmes are a minority in our sample, which suggests that a large proportion of programmes that we classified as accelerators or that self-identified as accelerators do not consider direct finance as one of their key contributions to startup success. A substantial proportion of 44% of startups received help with team formation, which is not typically associated with accelerators that usually select businesses with existing teams of founders for their programmes. This type of support may thus be more frequent and potentially more important than advertised by programmes.

Our findings are broadly in line with Aerts et al.'s (2007) sample of 107 European incubators. Incubators in their sample provide services similar to the ones we measure at a similar frequency. One notable exception is the provision of managerial training, which only 47% of incubators provide, compared with 84% or 85% of startups in our sample that receive coaching or business skills development.

Most startups were in contact with a mentor for up to two hours a week

Mentoring support is common in the programmes studied, although its intensity varies greatly between programmes (Appendix 5.8, Table A13). About 89% of startups receive mentoring support (242 out of 272 that answered the question). The majority of respondents are in contact with a mentor for up to 2 hours per week, while about 6% receive mentoring support for more than 9 hours per week.

There is not one typical way in which mentoring is offered by incubators and accelerators

Mentors are relatively evenly distributed between being industry experts (58%), entrepreneurs (both who have sold a business, 57%, and who have not sold a business, 51%), venture capitalists or business angels (45%), and consultants or business developers (67%), suggesting that there is not a single dominant way of providing mentoring in accelerators or incubators.

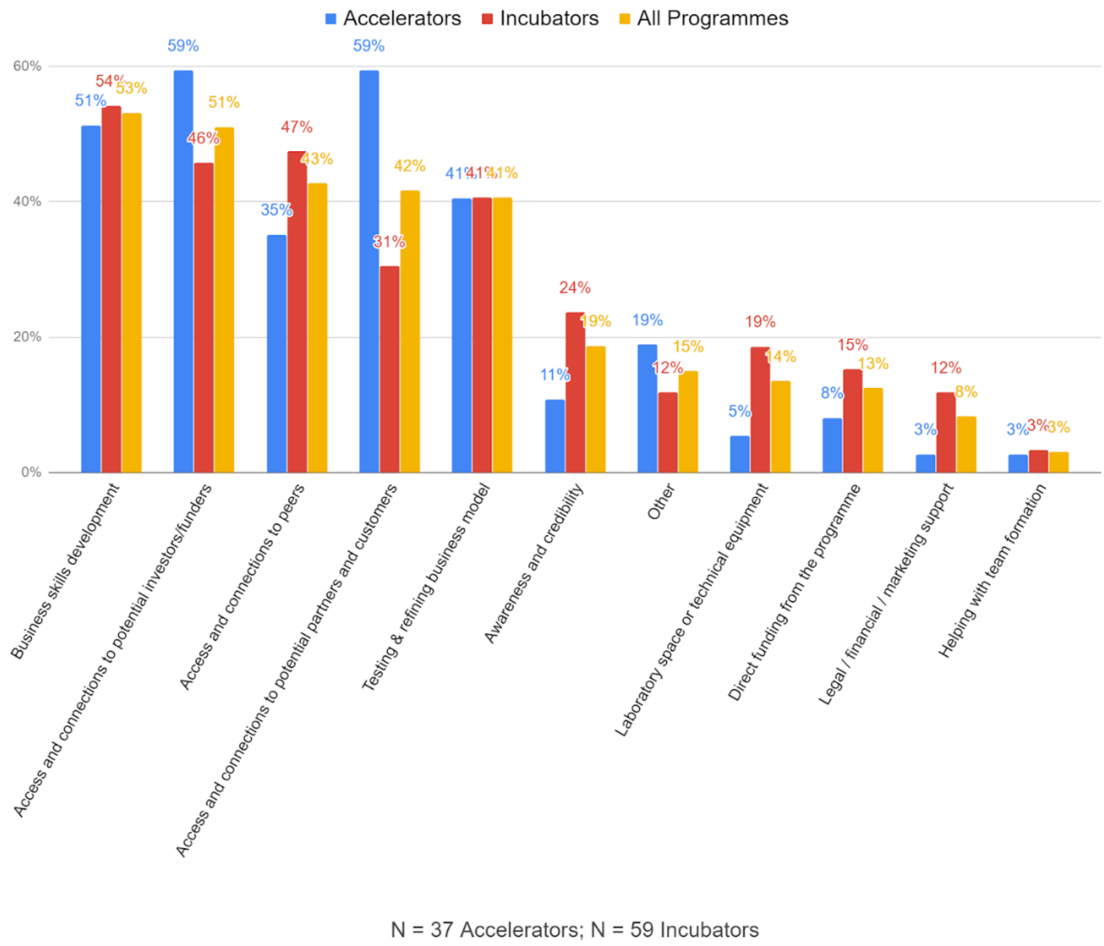
When investigating combinations of mentors, a large number of startups (27%) received concurrent mentoring support by experts, entrepreneurs, venture capitalists or business angels, and consultants. The second most common combination (9%) is mentoring by entrepreneurs, venture capitalists or business angels, and consultants, followed by business consultants or developers only (8%). This clustering of startups in certain combinations of mentoring support suggests that accelerators may have specialised mentoring models. Closer inspection of the data suggests, however, that this clustering cannot be observed at the accelerator level. In other words, programmes that provide one combination of mentoring support to some startups often provide another combination to other startups.

Incubators and accelerators perceive business skills development and access to potential investors to be there most important benefits to startups

In our survey of accelerator and incubator managers (see Section 3.11 for details about the survey), we asked respondents to select what they perceive to be the top three benefits of their programmes for startups (Figure 7). From the options we gave, the two most selected benefits are business skills development (53%) and access and connections to potential investors (51%). The least popular are direct funding (13%), legal, financial and marketing support (8%), and help with team formation (3%).

Accelerators are more likely than incubators to report ‘access to potential investors, partners and customers’ as one of their top three benefits. This could be due to the fact that a quarter of accelerators (compared to just 10% of incubators) offer startups a demo day, in which startups showcase their product or service to individuals and organisations that may want to fund or work with them. On the other hand, incubators more often report ‘access and connections to peers’ as a top benefit, which may be explained by incubator participants being in a shared space for longer time periods. Relative to other benefits provided, accelerators and incubators in the UK both place a greater emphasis on networking with similar businesses than European incubators (CSES 2002).

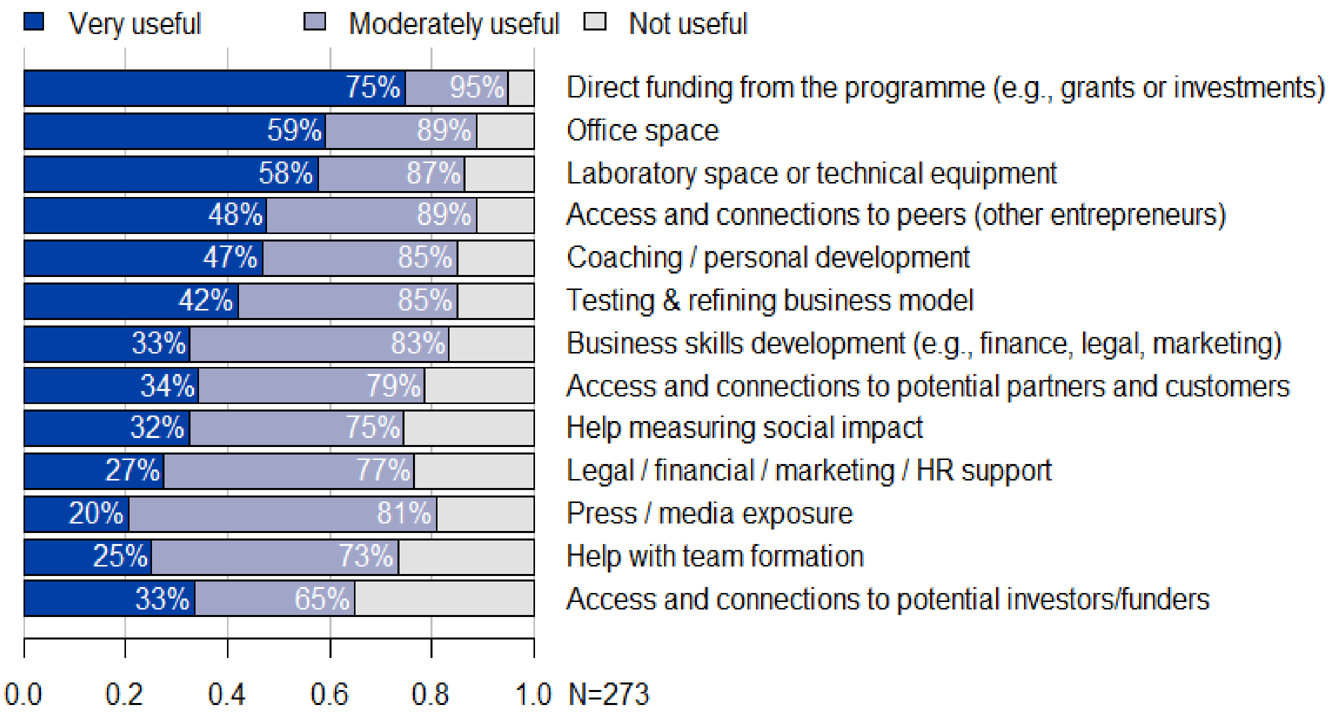
Figure 7: Importance of support types as perceived by programme



Startups perceive direct funding, access to office space, lab space and technical equipment to be the biggest benefits to participating in an incubator or accelerator

We also asked the startups we surveyed about how useful they found the support they received (Figure 8). Direct funding is most often reported as being useful, followed by access to office space, lab space and technical equipment. These are followed by access to connections and peers and coaching / personal development.

Figure 8: Perceived impact of support received by startups[38]



Although they are not directly comparable as questions are not asked in the same way, it is interesting to look at what incubators and accelerators see as being the key benefits of their programmes versus what startups see as being the most valuable elements of the programme they attended. For example, direct funding is thought of as most useful by startups but a lot less important by accelerators and incubators. Business skills development is also seen to be considerably more important to incubators and accelerators than to startups. While it is not clear whether it is programmes or the startups that participate in them that have the best view of which services provide the most value, where there appears to be most agreement is around the benefits associated with having access to other entrepreneurs (peers) that comes with participating in an incubator or accelerator.

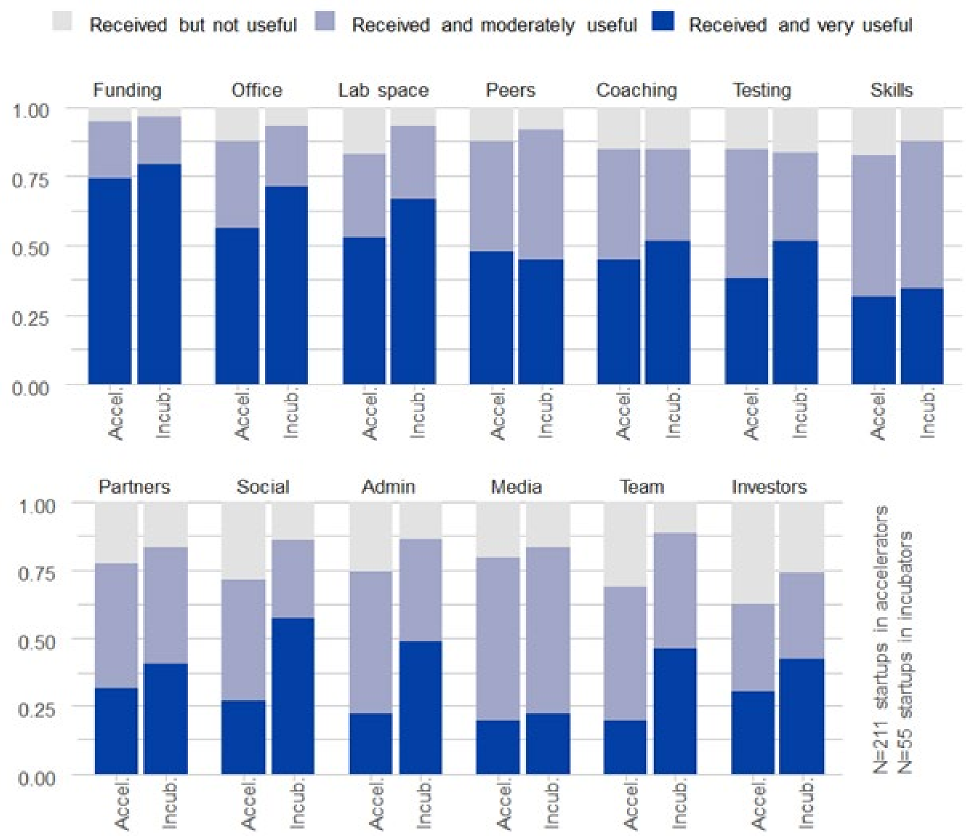
Our findings for UK startups are broadly in line with those for European startups participating in incubators (CSES 2002) but differ from those for a global sample collected by Emory University (GALI 2017). Emory University's Entrepreneurship Database Program identified network development with partners and customers as the most important contribution of accelerators, followed by access to investors or funders, mentorship by experts and securing direct funding. In our results, direct funding was seen as an important type of support, while access and connections to potential investors received the lowest average score. Tangible benefits, such as office space, laboratory space or equipment, are regarded important by startups. Surprisingly, startups in the UK valued access to peers much higher than their global counterparts, but both groups agree on the relatively small impact of media exposure obtained through the accelerator.

[38] Mentoring is not featured in this figure because survey respondents were not asked how useful mentoring was.

There is little difference between what types of support startups find most useful in incubators compared to accelerators

When looking at accelerators and incubators separately in Figure 9, differences in perceived impact by participating startups are relatively small for most support types, though incubators generally receive higher impact ratings by startups. An explanation for this finding is the typically longer duration of incubator programmes compared with a typical three or six-month accelerator programme. When we compare the proportion of respondents that consider the support not useful between accelerators and incubators, however, none of the individual differences in proportions is significant (at the 10% level of significance using Fisher's exact test) because of the relatively small sample size in the non-accelerator subsample.

Figure 9: Perceived impact of accelerators and other programmes by support type



Startups suggest less tangible changes in their confidence and mind-set are important benefits to participating in an incubator or accelerator

The importance of funding, networks and programme resources is mirrored in startups' free-text responses. We invited respondents to further elaborate on the effect that programmes had on their business and their experience of participating. Startups place a strong emphasis on networks with peers and an environment that fosters mutual support and a sense of community. Help in obtaining finance and mentoring support are also seen as important. Interestingly, several startups mention the strong intangible impact that programmes had on their confidence and mind-set as an entrepreneur. Respondents commented, for example, the programme "boosted my confidence", "it really stretched me and enabled me to be critiqued and ready for the real world" and "it did help me realise how much I hold myself back".

Startups often find programmes focus to heavily on short-term growth

In the free-text responses, a substantial number of startups reported a desire for programmes to have a greater long-term focus of programmes, which too often were said to focus on short-term growth, quickly finding investors or “ticking boxes”. Startups commented they “were pushed to investing into our business in order to scale it which it turned out was not a good idea” and “the goal of finding investment is perhaps weighted a bit too heavily over the goal of creating a profitable business” (Appendix 5.9).

It is important to note that the results discussed above reflect only what startups think were the most useful types of support they received and does not measure the effect of receiving a support type compared to not receiving it, results to this analysis are discussed below.

Startups which receive access to partners and customers, help in refining and testing their business model, and/or help with team formation are most likely to think the programme they participated in positively impacted their chance of success

To estimate the impact of support types on startups’ success, we study both perceived and objective measures of startup success. We construct this perceived contribution from answers to the question “looking back, what impact has the support provided by [programme name] had on this enterprise's chance of success?” It is important to note that here startups are being asked about how important they perceive the programme as a whole to have been to their success, rather than how useful particular types of support they received were, as was discussed in the previous Section.

In a second step, we aim to decompose the perceived impact into effects on objective measures of success. This second step serves two purposes: it validates the responses given by participants in our survey and helps to understand what factors are ultimately linked to objectively measurable startup success.

In our results in Table 2, we find that three support types are most strongly associated with the perceived impact of accelerators by participating startups: help with team formation, testing the business model and access to partners and customers. Startups also perceive accelerators more positively if they provide direct funding, administrative support, or when a mentor is an industry expert, though the effect is of these types of support is less strong as for those mentioned above. This result supports the earlier finding in which startups generally report direct funding as being very useful (Figure 8), but does not support the previous finding in which they do not perceive a similarly positive contribution from access to partners and customer and from help in with team formation. A possible explanation for this partial disconnect is a misattribution of support types to the overall contribution of the accelerator. Startups may perceive an overall positive value of the accelerator support but may not be able to accurately assign this contribution to certain support types.

Table 2: Summary of impact results. The table below shows the direction and significance of coefficients in our optimised models in Appendix 5.10. For example, "+++" represents a coefficient that is positive and significant at the p<0.01 level. Similarly, "++" is a positive coefficient at the p<0.05 level, and "−" is a negative coefficient at the p<0.1 significance level. Dependent variables are: Perceived impact of accelerators perceived by startups; employment growth; growth in the number of employees with a degree; progression to a higher stage in a firm life cycle; innovation of products, services or processes; patenting (probit model); R&D expenditures (Log); and whether any additional investment was raised since applying to the accelerator.

Dependent variable	Perceived impact	Employment growth	Employees with a degree	Development stage	Innovation	Patenting	R&D (Log)	Investment raised
Support by programme								
Access to partners & customers	+++							
Access to investors							+++	+++
Access to peers		+++	++					
Testing & refining business model	+++	−−−	−					−−
Help with team formation	+++	++		+++	+			
Direct funding from the programme	++	+++			+++		+++	+++
Business skills development								
Press or media exposure		+++				+++		
Lab space or equipment								
Legal, financial, marketing or HR support	+					−−	−	−−
Help measuring social impact			++					++

Dependent variable	Perceived impact	Employment growth	Employees with a degree	Development stage	Innovation	Patenting	R&D (Log)	Investment raised
Office space								
Coaching / personal development				−−				
Mentoring support								
Industry expert	+				++			
Entrepreneur (exited a venture)								
Entrepreneur (not exited)								
VC / angel		++	+++					
Consultant, business developer		−−−	−−		−	+		
Mentoring intensity		+				++		

Direct funding and help with team formation are positively associated with the greatest number of outcome measures

When we turn to the relationship between accelerator support and objective outcomes, again using data obtained through our startup survey, we find that a small number of support types explain most of the variation in outcomes. As well as being associated with the perceived impact by participating startups, the provision of direct funding is associated with employment growth, innovation, R&D expenditure and additional investment. Direct funding had a particularly strong effect, relative to the other types of support, on innovation. This can likely be explained by part of this extra funding being spent on R&D (as indicated by the positive relationship between direct funding and R&D expenditure), resulting in the firm innovating more.

Help with team formation is associated with a greater likelihood of advancing the startup's development stage and its innovation output, as well as the perceived impact by startups. The effect of team formation on startup stage was considerably stronger than for any other support type. This is unsurprising since team formation itself is a major step in the development of a startup.

The types of support perceived to be important by startups are often not the same as those that are associated with startups success

Not all support that is valued highly by startups is associated with startup success. Access to partners and customers, for example, is not related to any success metric tested in our models. Contrary to the positive impact perceived by startups, the effect of support in testing and refining the business model on growth and investment is negative. This can be explained, however, if accelerators help startups to discover a viable business model, which may involve rationalising and choosing between competing business models or developing new business models fundamentally different from the one at the time of acceptance into an accelerator.[39] Previous research has indeed found an increased likelihood of firm death as a result of attending an accelerator.

An alternative explanation from a limited resource perspective is simply that any time spent on refining and testing business models cannot be spent on growth and investment. It is possible however, that while not captured at the point of data collection, this activity may have longer-term effects.

A number of support types are associated with success metrics but not with perceived impact of programmes, for example, access to investors is positively related not only to investment but also R&D spending and media exposure is linked to employment growth. Furthermore, while mentoring by venture capitalists or business angels is positively associated with growth outcomes, mentoring from consultants or business developers has a negative association on growth (employees and development stage) but a positive one with patenting. These effects suggest that networks and exposure provided by accelerators generally improve startups' outcomes but need to be provided in a targeted way. Of some surprise is the finding that help measuring social impact has a positive effect on both the proportion of employees with a degree and investment raised, this may indicate that this type of support can help startups better tell their story and pitch both to skilled employees but also to investors. By contrast, access to peers and mentoring by venture capitalists or business angels are more directly related to growth without an effect on innovativeness.

Mentoring from a consultant or business developer may help startups focus on their current ideas rather than expanding into new markets

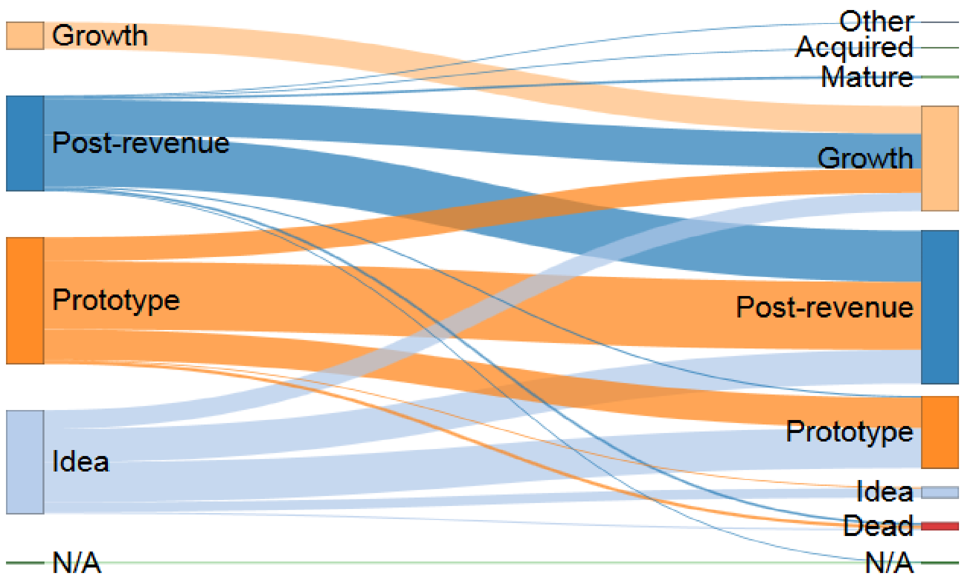
Our finding that mentoring from consultants or business developers has a negative relationship to employment growth but a positive one with patenting may suggest that consultants or business developers help startups focus and rationalise their business to maximise the market impact of existing ideas rather than develop entirely new products or services. A similar relationship was found with venture capitalists by (Lahr and Mina 2016), who attribute the positive relationship between venture capital on patenting to superior capabilities of venture capitalists to select investee firms with promising products in their early stages of patent applications.

[39] Accelerator participation increases the rate of exit by acquisition and exit by quitting in startups participating in programmes by Y Combinator and TechStars. Smith and Hannigan (2015) speculate that this is due to mentoring and peer influence.

Negative association between coaching and development stage may be the result self-selection by startups

Since joining a programme, many startups advanced to the next stage in their life cycle while only a few reverted to an earlier stage (Figure 10).[40] We find a negative relationship between coaching and development stage. One would not normally expect a detrimental effect of coaching or personal development on startup success. However, this negative effect may be explained by startups self-selecting into programmes that offer coaching if they perceive a need for personal development before they can advance their firm to the next stage of its development. Additional tests in a wider research setting could provide more insights into this hypothesised selection effect.

Figure 10: Development stage transitions. The startup's development stage at the time of its application to the accelerator is shown on the left, it's development stage today on the right. Percentages are available in Appendix 5.10, Table A25.



The intensity of R&D and patenting activity, and the likelihood of them being observed at all, are associated with different support types

Results for patenting and R&D expenditures are sensitive to the measurement of the outcome variable. The intensity of a startups patenting activity is positively related to whether they received media exposure through a programme and whether a consultant mentored them, both of which are associated with an increase in patenting output of about 1.2 patents (Appendix 5.10, Table A21). If we model patenting as a binary yes/no decision, two more variables significantly predict whether a startup patents: every doubling of mentoring intensity is associated with roughly a 5% increase in likelihood of patenting. Receiving administrative support, however, is associated with about a 15% decrease in the likelihood.[41]

For R&D expenditures, results are similarly dependent on how the outcome is measured. Direct funding through the programme is important for both the amount of expenditure and whether the startup engages in R&D at all. However, the amount of R&D expenditure is also positively related to whether the startup receives access to investors through the programme

[40] Most firms are located on or above the diagonal in the stage transition matrix in Appendix 5.10 Table A25, which indicates progress along the life cycle of a firm.
[41] Also if patenting is modelled as a negative binomial process, access to investors and coaching improve outcomes while testing the business model, skills training and office space reduce patenting activities.

(positively). The likelihood of observing any positive R&D expenditure, however, increases with the availability of office space but decreases with the provision of lab space. The latter may be due startups being able to reduce R&D expenditures by using lab space provided free of charge, rather than reflecting less R&D activity. These findings suggest that there may be different sets of drivers at play for the intensity and likelihood of observing patenting and R&D.

It is important to note here that it is not clear from this analysis which direction causality runs. For example, while the positive association between media exposure and patenting, discussed above, could be taken as evidence that by giving startups media exposure programmes increase their ability to patent, it is perhaps more plausible that instead those startups that are patenting go on to get media exposure through their programme because of these patents and the innovations they represent.

Provision of physical space and equipment may be less important than other support types

When looking at the overall effects of support types in Table 2, startups that have access to office space, or laboratory space or equipment do not seem to perform better than those that do not receive this type of support. This finding suggests that startups can obtain these resources relatively easily outside accelerators and incubators. While the provision of these resources, as such, does not suggest a competitive advantage of accelerators or incubators in providing them, the availability of space enables other benefits that are strongly related to a physical space such as interactions with other founders and entrepreneurs.

There is not one specific mix of startup support that is positively related to multiple outcomes measures

Do different types of incubators and accelerators have different effects on startups? The terms “incubator” and “accelerator”, hide the large amount of variation that exists within these models. Various classification systems have been developed over time (e.g. Allen and Mccluskey 1991; Grimaldi and Grandi 2005; von Zedtwitz and Grimaldi 2006; Becker and Gassmann 2006). These typologies distinguish different types of programmes based on several factors including: whether they are for-profit or non-profit, the type of parent organisation they are run by (e.g. property developer, venture capital, academic/university) or their purpose (e.g. ecosystem builder, deal-flow maker and welfare stimulator; Pauwels et al. 2016; Clarysse et al. 2015).

We want to understand the effect of programme type on their impact. Rather than impose a pre-conceived typology on our sample of programmes, we identify six different programme types by identifying commonalities in the support they offer (see Appendix 5.11 for analysis):

- High-intensity support: frequent offer of all support and mentoring types
- Accelerator-like: mix of all support types, but less intensive on team building, funding and mentoring
- Mentoring-free: all support types with a focus on team building, but very limited mentoring
- External exposure: medium support and light mentoring, focus on media and press exposure
- Mentoring focus: light-touch support, but focus on mentoring by entrepreneurs, VCs and experts

- Incubator-like: coaching, skills, office and admin support, little external engagement

As expected from our sampling strategy, a typical accelerator (class 2) is the most common class, with about 42% of respondents showing a moderately high likelihood of receiving a combination of all types of support. About 19% of respondent receive intensive support on all measures (class 1). A smaller but still substantial proportion of startups receive support that may be typical for incubators, with an emphasis on coaching and startup development but less on external engagement (class 6). The three least frequent combinations strongly vary in their mentoring content and external engagement and may reflect specialised programmes or startups requiring only limited support.

When comparing “high-intensity support” programmes to the other five programme types we find significant effects ($p<0.05$) for only two outcomes: perceived impact and R&D expenditures. For the ‘external exposure’, ‘mentoring’ and ‘incubator-like’ programmes, the perceived impact of the programme is lower compared with the high-intensity type. For R&D expenditures, all programme types are inferior to the high-intensity type, except for ‘external exposure’ type; for which there is no significant difference. Surprisingly, however, none of the other outcomes are significantly related to any programme type, which suggests that there is not a generic recipe for startup support that improves success across a range of outcomes.

The impact of different support types may be dependent on whether they are provided through an accelerator or an incubator model, however, the sample size used in this study is too small to draw firm conclusions

As a robustness test, we estimate the impact of support for the subset of startups in programmes that we classify as accelerators. The relatively small number of startups in incubators prevents a separate analysis of these programmes. We can test, however, whether results change if we exclude incubated startups from the sample and rerun our analyses estimating the impact of startup support.

Results for the accelerator-only sample retain most of the effects found for the full sample despite an expected loss of significance due to the reduced sample size (Appendix 5.10, Table A24). Moreover, some new effects are now significant, which suggests that startups attending accelerators are more similar to one another than other startups. Effects for direct funding and help with team formation in particular remain significant. Our model for the perceived impact of programmes on startups now also shows the positive association with access to investors, business skills development and mentoring by entrepreneurs. Similarly, access to partners is now positively associated with the development of startups. This suggests that while these things may not have a positive relationship in the setting of an incubator, in an accelerator they do.

Some negative effects are more pronounced in the reduced sample. The provision of office space is now negatively associated with innovation, mentoring by an entrepreneur who has not exited a company yet has a negative relationship with the likelihood of advancing to the next development stage, and patenting performance is negatively associated with access to partners and customers. Some of these effects are difficult to reconcile with what we know about entrepreneurial processes but may be statistical artefacts caused by correlation among different types of startup support. To reliably distinguish effects and rule out spurious results, a larger sample would be needed.

3.5 Through which mechanisms does support have impact? A theory of change

3.5.1 Methods

Previous authors have pondered whether "[p]erhaps no general theory is possible because the causes and consequences of science parks and incubators may be idiosyncratic to their geographic locations, political and social contexts, and economic systems" (Phan et al. 2005). Whilst such contextual factors certainly make it difficult to determine what works for what types of firms, we believe that the evidence base is gradually building, thus enabling the construction of theoretical models of how incubators and accelerators achieve impact.

Accelerators and incubators affect startups in numerous ways. Outcomes of such interactions manifest themselves sometimes immediately and sometimes only a considerable time after a startup has graduated from a programme. In this Section, we aim to investigate the pathways through which programmes may cause desirable outcomes for startups and society by combining our results on final outcomes above with additional analyses of intermediate outcomes.

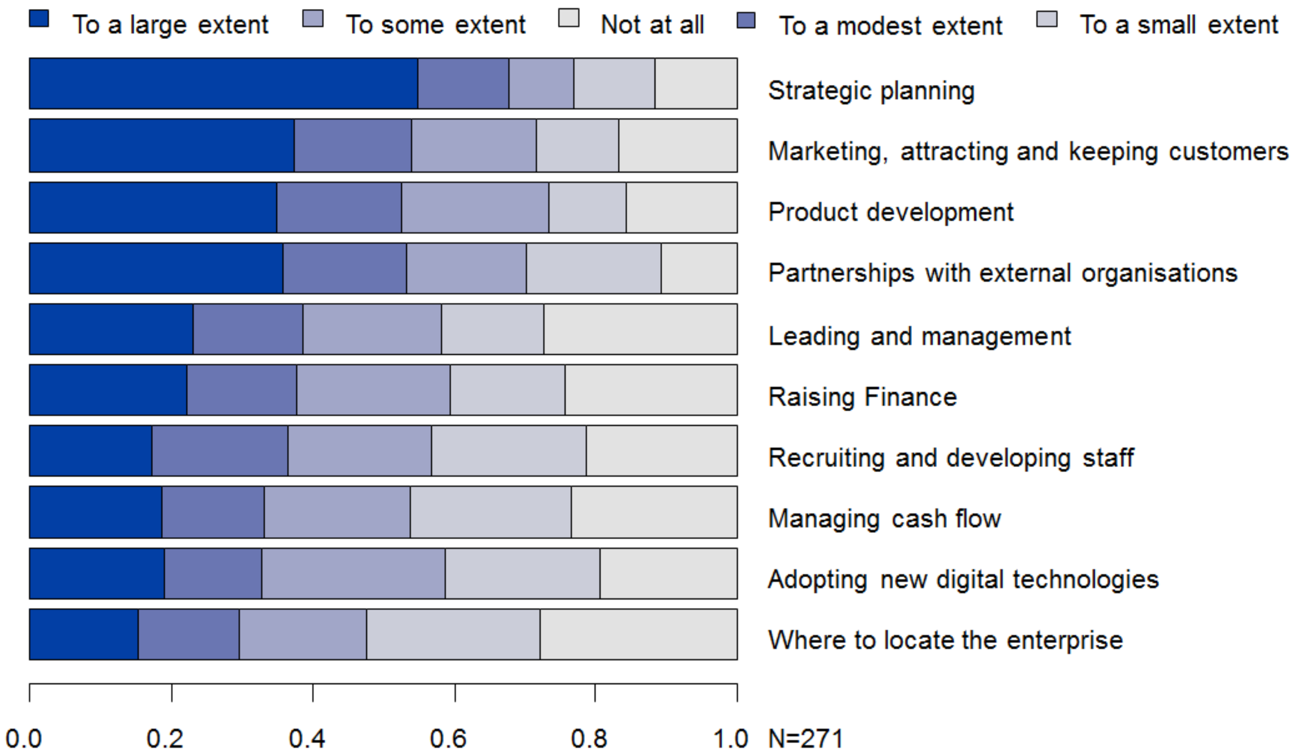
Our previous analyses used regression models to relate support provided by programmes directly to ultimate outcomes, treating the startup and its transformation while participating in a programme as a black box. To further investigate the mechanisms by which support may lead to ultimate outcomes, we again draw on data from our startup survey (see Section 3.21 for details) in which we asked startups whether they changed their way of doing business while participating in an accelerator or incubator programme. Changes in business practices explain a substantial proportion of the variation in productivity across firms and countries (McKenzie and Woodruff 2015). Whilst not necessarily desirable outcomes themselves, they may lead to beneficial outcomes later and can be visible much earlier, which provides for a closer link with startup support. In view of their position in the pathway between startup support and ultimate outcomes, we call these variables intermediate outcomes. To study potential pathways through which startup support affects outcomes, through a series of regression models, we first analyse which support types are associated with changes in intermediate outcomes. In the second step in our pathway analysis, we estimate how intermediate outcomes relate to ultimate outcomes. This stage helps to uncover potential mediators - variables in the pathway from startup support to ultimate startup success.

3.5.2 Results

The most common intermediate outcome related to accelerator or incubator participation involves startups changing their approach to strategic planning

Figure 11 below illustrates the intermediate outcomes, measured by respondents' answers to the question "Since applying to [programme name], to what extent have you changed your approach to: [intermediate outcome]". For each intermediate outcome, the graph shows the proportion of startups for each degree of change. This figure shows that most change within startups, since participation, occurs at the strategic level. Marketing, product development and external relationships are viewed as important areas of change, whereas other common business functions, such as finance or human resources, are not as often the focus of change since participation in an accelerator or incubator programme. The small proportion of startups reporting a change in their decision of where to locate the business corroborates evidence from the relatively small number of actual relocations of startups that we observe in our sample.

Figure 11: Change in business practices



While several support types are associated with at least one intermediate outcome, help with team formation is related to all that were measured

Results from regression analyses suggest that if a programme offers help with team formation, startups report changes in a wide range of intermediate outcomes (Appendix 5.12, Table A28). This is not surprising as changes to the team of founders and early-stage employees often affects the business in dramatic ways, especially when startups are still in the process of defining their business model. Access to business partners and customers is related to changes in strategic planning and external partnerships, which again seems plausible given the knowledge transfer that typically occurs through close links with business partners. Among the support types with two or more strong links to intermediate outcomes, coaching and personal development is related to changes in strategic planning and marketing, as well as leadership and management, which suggests that personal training and support may help entrepreneurs to more effectively manage their business. Business skills development, however, has an insignificant or even negative effect on intermediate outcomes, in line with our findings for its effect on ultimate outcomes.

Relatively few intermediate outcomes are associated with startup success, but of those that are, changes to how startups approach raising finance is related to the greatest number of ultimate outcomes

The analysis suggests that relatively few intermediate outcomes are associated with improved outcomes for startups (Appendix 5.12, Table A29). Changes in the way in which startups raise finance are related to several desirable outcomes, and changes in recruiting practices is the only other variable with more than one significant effect (at $p<0.05$) on ultimate outcomes. Interestingly, several intermediate outcomes, such as changes in product development, marketing, location decisions, or the adoption of digital technologies, are uncorrelated with ultimate outcomes at this level of analysis. These findings may be a reflection of large direct (unmediated) effects of startup support or hidden mediator variables that would need to be found if the pathways discovered in our analysis seem incomplete or not ideal for policy interventions.

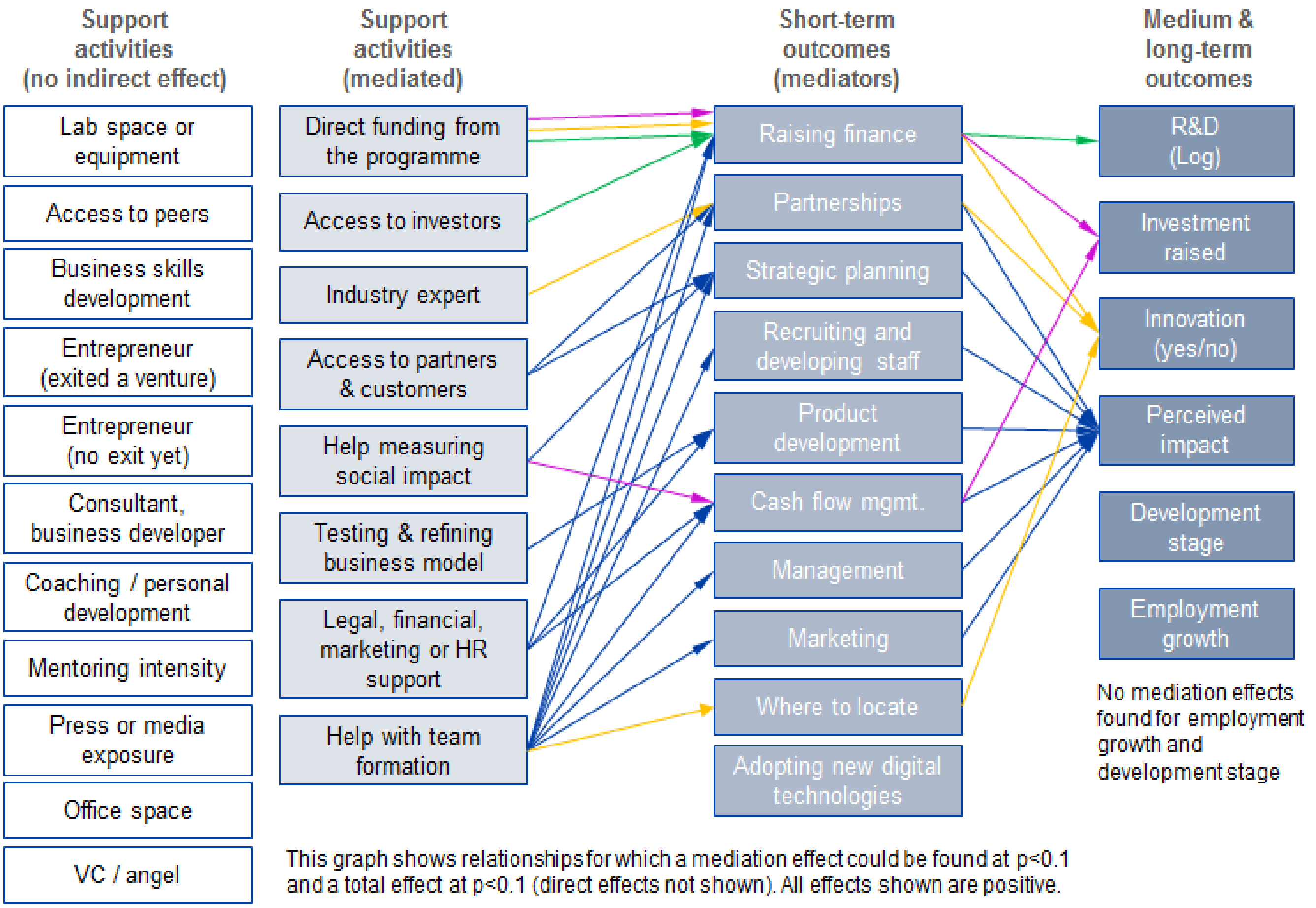
The two sets of analyses establishing pathways from a support measure to an intermediate outcome variable (Table A28) and pathways from intermediate to ultimate outcomes (Table A29) are useful to understand the processes by which startups become successful. A combined pathway from a support measure to an intermediate outcome to an ultimate outcome should only be taken as evidence of a mediated relationship if an overall effect of this support on the ultimate outcome can be found (omitting the intermediate outcome from the estimation). For example, our results suggest that access to partners and customers, coaching, and being mentored by an entrepreneur who has exited a business are associated with changes in strategic planning (Appendix 5.12, Table A28), while changes in strategic planning lead to greater perceived impact of accelerators (Appendix 5.12, Table A29). In our reduced-form analysis (Table 2), however, we find that of these support types only access to partners and customers has an overall effect on the perception of impact.

While some types of support offered by programmes appear to be directly related to startup outcomes, others are mediated by changes in startup behaviour

Formal mediation tests reveal that of the outcomes measured, the perceived impact of an accelerator or incubator by participating startups is associated with the widest range of intermediate outcomes (mediators; Figure 12). Most of these intermediate outcomes, such as changes in partnerships with external organisations or changes in strategic planning, mediate the effect of one support activity: help by the programme to build the startup's team. This result underlines our earlier finding that team formation has the potential to fundamentally transform the business through multiple pathways.

Several pathways appear to lead to increased innovation output. Changes in a startup's approach to raising finance is typically accompanied by an increase in their innovativeness. External partnerships are similarly important to a startup's innovation output, as is the decision where to locate the business. We observe greater reported success in raising finance if startups also report change their approach to raising finance and to managing cash flow. Finally, R&D expenditures are related mainly to a startup's approach to raising finance, which suggests availability of finance as the underlying determinant of a successful R&D strategy. The two remaining key outcomes variables, employment growth and progress to the next development stage, are not associated with any of the changes in business practices we asked about. However, several support activities are directly related to startup success in these two dimensions, such as help with team formation, direct funding through the programme or access to peers (Table 2).

Figure 12: Pathways from support activities to startup success. Mediation relationships between startup support, changes in business practices and ultimate outcomes. We test whether the startup support variables act indirectly through the intermediate outcomes (i.e., potential mediators). The pathways shown are derived from individual mediation models testing one mediator and one support activity at a time (see Appendix 5.12, Table A28), in addition to variables already present in optimised models for the outcome variable and mediator (see Appendix 5.12, Table A29). The graph shows an arrow connecting treatment variables (startup support activities), intermediate outcomes and medium/long-term outcomes wherever an average mediation effect at a significance level of p < 0.1 and a total effect at the same level of significance can be found. Variables without significant mediated paths are shown without connecting pathways but may still have direct effects on medium/long-term outcomes. Colours of connecting paths indicate which support activities and intermediate outcomes are associated with each medium/long-term outcome.



The main limitation of this analysis is the large number of possible pathways relative to the number of startups in our sample. Correlations among support activities and among mediators may cause models to attribute the same effects to multiple support activities if these activities are highly correlated. For example, the positive relationship between help with team formation and perceived impact may act through any or all of the intermediate outcomes tested, but the analysis does not allow us to remove the spurious ones. With a substantially larger sample, most or all of the possible pathways could be tested simultaneously in a structural equations model.

In summary, we find that startup support appears to act on ultimate startup success both directly and indirectly through intermediate outcomes. However, substantial indirect pathways can only be found for about half of the potential mediators and four out of the six ultimate outcomes we test. Access to direct funding through the programme and help with the formation of the startup's team appear to contribute to startup success through a variety of pathways. Other support types act more directly on desirable outcomes. Access to peers or coaching, for example, does not seem to be mediated but still have a considerable direct impact on outcome variables as demonstrated above.

While most mediation effects are the same when accelerators are analysed separately from incubators, there are a few notable differences

One might ask whether pathways are different if we study only startups that participate in an accelerator and remove all other startups from the sample. Results of this analysis are shown in Appendix 5.12, Figure A5. While most effects remain the same compared with the full-sample analysis, including the positive relationship between access to funding, team formation and changes in financing and strategic planning practices, there are a few notable differences. On the outcome side of the equation, effects on employment growth are mediated by two business practices: raising finance and recruitment. We further identify one effect on startups' development stage that is mediated by changes in cash flow management. Among mediator variables, the decision where to locate the business does not mediate any effects in the accelerator-only sample, but startups' approach to adopting new digital technologies now mediates part of the effect of team formation on perceived impact.

3.6 What is the impact of incubators and accelerators on the wider business ecosystem?

3.6.1 Methods

To explore the effect of accelerators on the wider business ecosystem, we estimated the effect of accelerators being launched on the amount of venture capital invested in that region. The main empirical challenge is the non-random launch of accelerators: these programmes are possibly founded in regions and periods with higher startup activity potential.

We assemble a dataset with information on the dates when business accelerators launched across different regions (at the local authority level) in the UK. We focus on local authorities (as these approximate the likely range of influence of accelerators)[42], and particularly on those local authorities outside of London, where the potential impact of accelerators in regional development is likely to be most meaningful. We also restrict the sample to local authorities whose first accelerator was launched prior to 2017 (in order to have at least one full year of data after the launch). The dataset is derived from the Directory of Accelerators created by Nesta in 2017.[43] There are a total of 18 programmes that were founded in 17 local authorities in the UK between 2010 and 2016. We note that some of the local authorities in the list had more accelerators launched after the accelerators listed in the table. For the purpose of this exercise, we ignore these additional launches and focus only on the first year of arrival of an accelerator programme into the regions.

We combine this dataset with information on venture capital fundraising for the same regions, in the years before and after the launch of accelerators. We then organise the dataset in "event time", where each event refers to the year in which the first accelerator was launched in a

[42] The average land area of the 17 boroughs observed is 62 sq miles. However, as these include both cities and more rural areas, the size of varies quite a bit, from 29 sq miles (Nottingham City Council) to 223 sq miles (Vale of White Horse District Council).

[43] Appendix 5.13, Table A30 shows the names and locations of accelerator programmes in the sample.

particular region. For each local authority in the sample, we create an event-time variable τ indicating the number of years to/since the region's first accelerator launch, and an indicator variable Post indicating the period after the region received its first accelerator

Our analysis focuses on venture capital fundraising, obtained from Beauhurst,[44] as a key outcome variable. First, we measure the number of distinct seed venture capital deals that occur each year in each local authority (number) separately for companies in the "high-tech" sector and in the "non-high-tech" sector.[45] We make this distinction as accelerator portfolios concentrate in the high-tech sector (77% of the 5,284 accelerator portfolio companies in the Beauhurst data are classified by Beauhurst under this category). Second, we code the total sum of seed venture capital pounds invested each year at the local authority level (amount) separately for the high-tech and the non-high-tech sectors. Finally, we also adjust outcome variables to exclude observations for the accelerator portfolio companies. The resulting sample is a panel with observations at the local authority cross year cross sector level (i.e., high-tech and non-high-tech).

We attempt to help separate the impact of accelerator formation from the endogenous selection of accelerators into "hot" regions for entrepreneurship, by exploiting the staggered formation of accelerators across regions, and the treatment focus of these programmes on the early-stage high-tech sector. In detail, for a given region, we compare changes in early-stage venture capital activity in the high-tech sector, relative to the non-high-tech sector, before and after the first accelerator launch. The staggered launch of accelerators across regions implies that the implicit control group are the local authorities that do not experience an accelerator launch in the same calendar year of accelerator formation, even if they have already had their first accelerator launch or will have their first accelerator launch later on (see for example, Bertrand and Mullainathan 2003). We do not rely on synthetic controls (i.e., regions that did not have an accelerator launch during the sample period) for our estimation, as regions with and without accelerators differ substantially (Fehder and Hochberg, 2014). See Appendix 5.13 for further details about the approach taken and summary statistics. We do not control for any time-varying variables at the local authority level (e.g. startup activity), as most of these are outcomes of the accelerator formation event. Therefore, we cannot separate the effect of accelerator formation from the effect of other changes that occur at the same time as the accelerator formation but are not related to the event. The identification assumption is that the endogenous selection of accelerators across regions follows the general patterns in innovation opportunities for entrepreneurship, rather than systematically anticipates specific trends in the early-stage, high-tech sector, which is consistent with informal evidence on accelerator formation (cf. Fehder and Hochberg 2014). For the interpretation of results, it is important to note that any positive (negative) spillovers of the accelerator outside of high-tech will have the effect of dampening (biasing upwards) our estimates.

[44] Beauhurst is a searchable database of the UK's high-growth companies: they track every company raising equity, graduating from an accelerator, receiving an innovation grant, spinning out from a university and more.
[45] High-tech includes companies working in the following sub-sectors: Clean energy generation, Energy reduction technology, Other CleanTech, Chips and processors, Consumer electronics hardware, Internet and networking hardware, Mobile and wireless hardware, Server hardware, Other hardware, Pharmaceuticals, Research tools / reagents, Materials technology, Clinical diagnostics, Medical devices, Medical instrumentation, Nanotechnology, Desktop software, Embedded software, Internet platform, Middleware, Mobile apps, Server software, Software-as-a-service (SaaS), Other software, Other technology/IP-based businesses. Non-high-tech includes all others.

3.6.2 Results

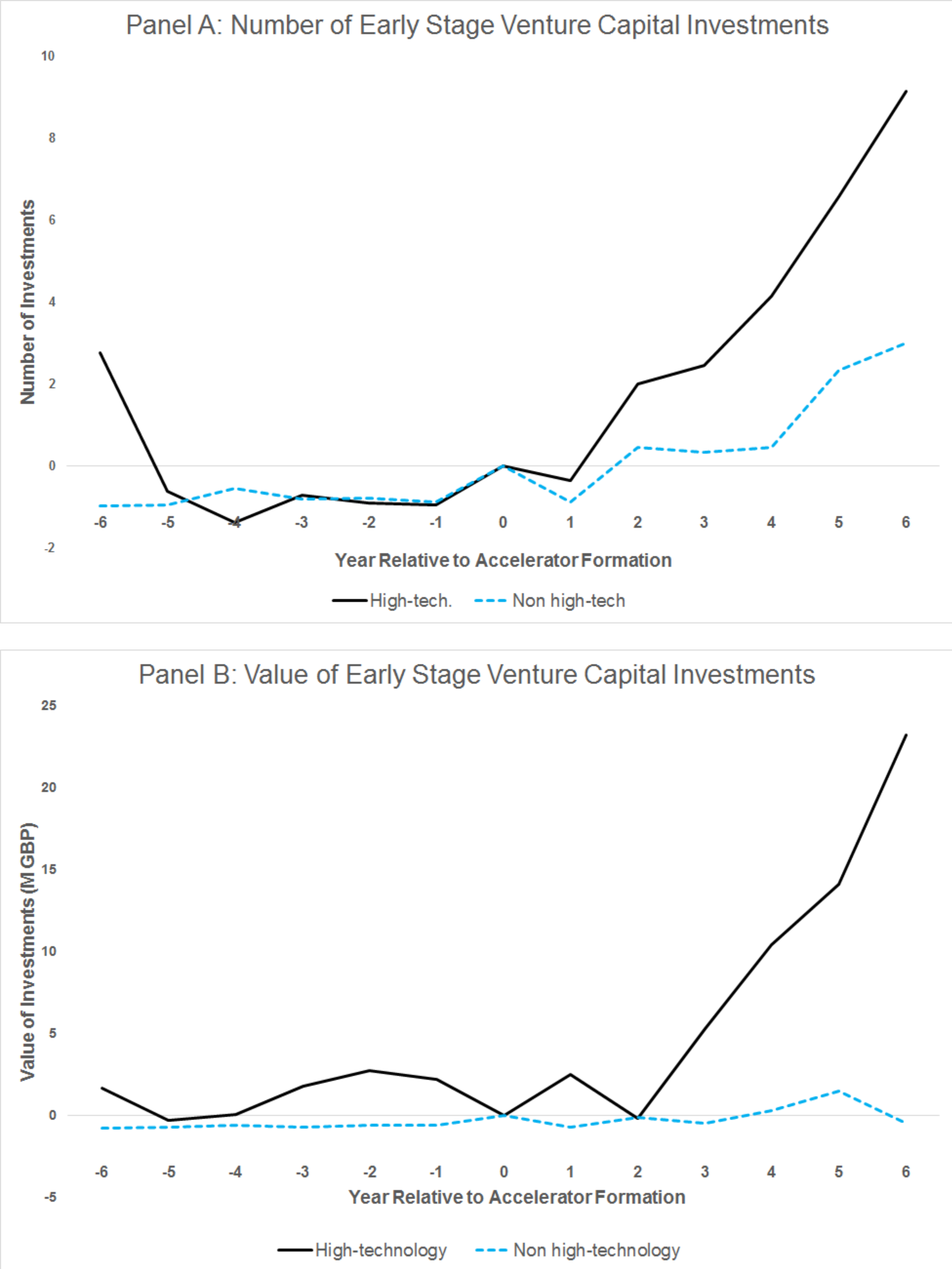
Accelerators have positive spillover effects on the wider business ecosystem

After the first arrival of an accelerator to a UK local authority, the subsequent pattern of VC investments varies between firms in the high-tech sector and those in the non-high-tech sector. Figure 13 shows evidence of trend breaks in the number and value of seed investments by VCs in high-tech companies. Instead, no trend breaks are visible for seed investments by VCs in non-high-tech companies. Figure 13 plots the point estimates of simple event time regressions around the arrival of accelerators to UK local authorities during the 2010-2017 period, which are estimated separately for the high-tech and the non-high-tech sector.

We show that the relative trend breaks are statistically significant ($p<0.05$) using a regression model that compares the patterns of seed investments by VCs in high tech and in non-high-tech around the first arrival of an accelerator to a UK local authority (Appendix 5.14, Table A32b). Our estimates imply that within 5 years of accelerator formation in a given region, an additional £48 million (26 deals) are invested in the high-tech industry, relative to the non-high-tech industry. This corresponds to an estimated increase of 243%.[46] Importantly, our results show that this increase in investment is not driven by investments going to accelerated firms. This suggests that, as was previously found by Fehder and Hochberg (2014) in the US, accelerators in the UK increase the exposure of non-accelerator companies to investors; as well as helping accelerated startups raise funding. Accelerators can help increase entrepreneurial activity in a region through different mechanisms, such as social events open to non-participants like weekly happy hours.

[46] The average annual venture capital investment into a region is £2.79 million, which implies an average investment in a five year period of £14 million. Our estimate of £48 million corresponds to a 243% increase over this average.

Figure 13: Accelerator Formation and Early Stage Venture Capital Investments. The figure plots results from estimating equation (1) separately for high-tech (solid line) and non-high-tech (dotted line) industries (see Appendix 5.13).



3.7. How do Local Enterprise Partnerships (LEPs) interact with accelerators and incubators in their region, and can these interactions help both parties reach their objectives?

3.7.1 Methods

In order to explore the relationship between Local Enterprise Partnerships (LEPs) and accelerators and incubators in their regions, we conducted semi-structured interviews with 22 out of the 38 LEPs in England. Care was taken to ensure that LEPs that were interviewed were geographically spread across the country. We asked interviewees questions about how they interact with programmes in their area, what the main barriers are to interaction, and how they could be supported to interact more effectively with accelerators and incubators.

3.7.2 Results

Below we summarise the key findings from interviews with 22 LEPs:

LEPs interact frequently with publicly funded incubators and accelerators but less frequently with privately funded programmes

Most LEPs we interviewed interact with incubators and accelerators on a regular basis, including by funding programmes or sharing staff as well as more informally such as by attending demo days and other events. However, interaction was much less common with privately funded programmes than those with university or other public funding.

Several LEPs explicitly mention incubators and accelerators in their strategic economic plans within their local industrial strategies. One LEP has also gone as far as to launch their own technological accelerator brand and is forming plans to create an accelerator and incubator space, with funding from ERDF and the local Authority.[47]

They would like to be given a bigger role in the strategic planning of incubators and accelerators in their regions

It is felt by LEPs that there is often a lack of strategy from the ground up, with accelerators and incubators being set up in regions without much consultation with LEPs, who believe they can help avoid duplication of efforts and ensure new programmes meet the region's needs and ensure they fit in with the local industrial strategy e.g. by influencing sectoral focus and design of programmes.

LEPs see challenges around the uncertainty in the sustainability of programmes, the lack of support for later stage businesses and how programmes might be funded if/when EU funding is withdrawn

Uncertainty about the sustainability of current incubator and accelerator programmes is seen to be a major challenge by LEPs. There was also a concern that while accelerators and incubators provide support to early stage businesses there is a lack of flexible workspace and support for later stage scaling firms. Finally, many incubators and accelerators are EU funded which raised questions about how these programmes will be funded if/when this money is

[47] Worcestershire’s LEPs BetaDen accelerator.

withdrawn following Brexit. In particular LEPs want to understand the extent to which the UK Shared Prosperity Fund will replace this funding.

There is a strong desire to learn from other LEPs

Most of the interviewees report a strong desire to learn from other LEPs either through online reports and case studies or through opportunities to connect directly with other LEPs to share experiences and best practices in running and working with accelerators and incubators. In order for this to happen interviewees report a need for more resources devoted to cross LEP working, noting that Growth Hub meetings, which are supposed to meet this need, have become very irregular.

3.8 What barriers do accelerators and incubators face in maximising their impact and what can be done to overcome these?

3.8.1 Methods

In our survey of incubators and accelerators (see Section 3.11 for details about the survey), we asked about the barriers they faced to having a greater impact.

3.8.2 Results

Incubators and accelerators see the cost of financing programmes as the biggest barrier to having more impact

The only barrier that is consistently reported to be restricting their impact to a great or very great extent is the cost of financing the programme (37% of programme managers; Figure 14); this barrier was experienced particularly extensively by accelerators.

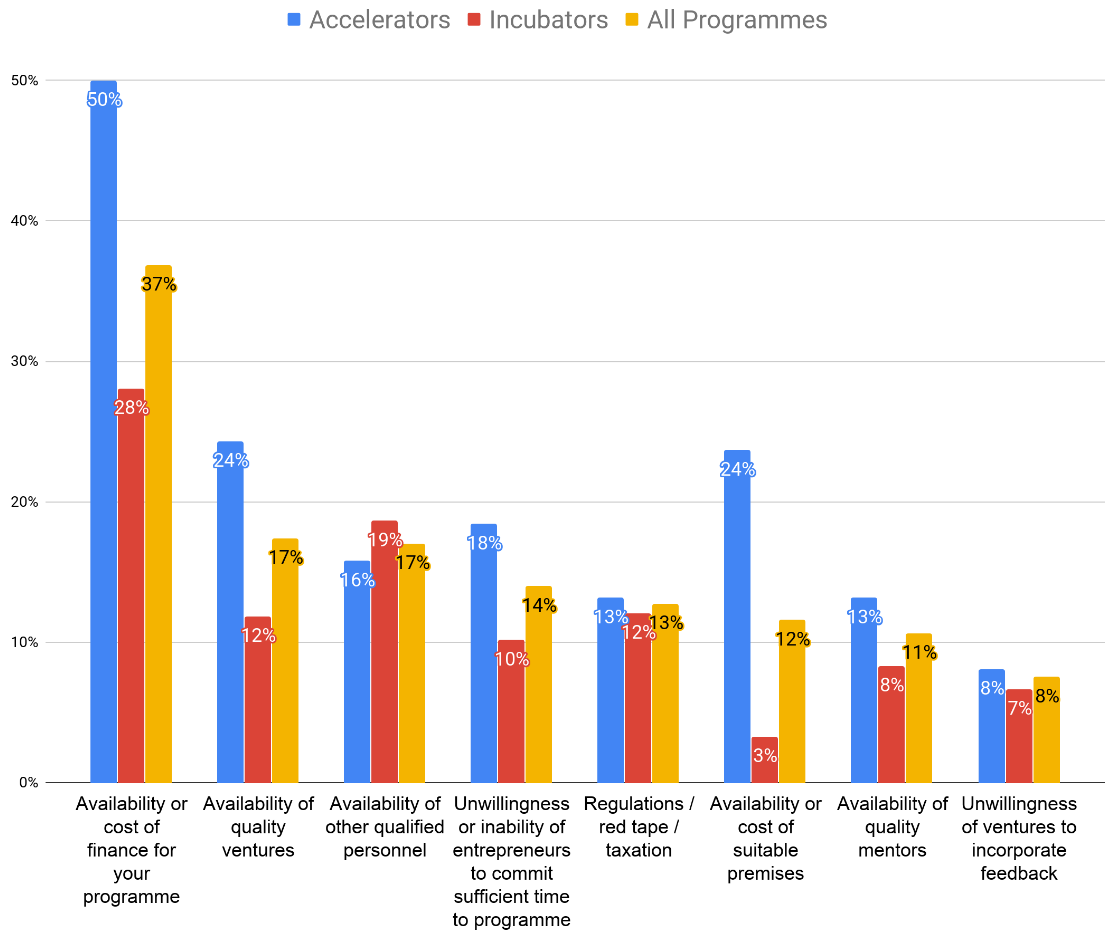
This is acutely felt by London-based programmes, with 47% of them regarding cost of finance as a barrier to a great or very great extent. Furthermore, 21% of programmes in London report the cost of suitable premises to be a barrier, above the 12% average for all programmes. It is perhaps unsurprising due to the general costs of operating in London, including how staff wages will be higher.

Availability of quality ventures and availability or cost of suitable premises is also seen as being a large barrier to accelerators

Accelerators also report availability of quality ventures and availability or cost of suitable premises as restricting their impact to a great or very great extent considerably more often than incubators do. The availability of quality ventures is likely to have a larger impact on accelerators than incubators because of the faster turnaround time of these programmes meaning that they more often are having to recruit new ventures. The availability or cost of suitable premises is perhaps harder to explain, but may be due to the fact that accelerators are more often located in the centre of large cities (particularly London), rather than in out-of-town science parks or university campuses.

Other barriers such as the availability of other qualified personnel, unwillingness or inability of entrepreneurs/ventures to commit sufficient time to programme, regulations/red tape/ taxation, availability of quality mentors and unwillingness of entrepreneurs/ventures to incorporate feedback are also mentioned by both accelerators and incubators but are less common.

Figure 14: Barriers to impact (% reporting a 'great' or 'very great' restriction on impact)



N = 38 Accelerators; N = 61 Incubators

4. Conclusions and discussion

4.1 Summary of findings

This study shows, through a survey of startups, that in general incubator and accelerator participants view these programmes as having a positive effect on their success. Participating startups perceive incubators as being slightly more important to their success than accelerators, though this perceived difference between incubators and accelerators may reflect the larger time commitment with the former – the average residency of an incubator being two years, compared with around six months for the average accelerator programme.

Enquiring about startups' perceptions of programmes is not, however, a robust method of judging their impact. In order to produce more robust evidence of the possible impact of support programmes, we examined startups from a notable corporate accelerator that provided participants with various elements of entrepreneurship schooling but no cash. We used a regression discontinuity design to compare firms that were just above and just below the threshold for being interviewed to compete for a position in the programme. Our main assumption is that firms ranking closely to either side of the interview threshold face similar innovation opportunities. The results from this analysis provide compelling evidence that the programme in question had a positive impact on survival, employee growth and funds raised. Moreover, since the corporate accelerator provided no funding to participants, the results point specifically to the provision of non-monetary services as a particular pathway to accelerators' impact, which is consistent with the results in prior academic work (Gonzalez-Uribe and Leatherbee, 2017; Gonzalez-Uribe and Reyes, 2019).

The findings from this study cannot be uncritically extrapolated to all programmes, since we know not only that programmes can vary significantly in terms of their content and methods, but also that the local context (such as university affiliation or competitiveness of the local business environment) seems to have a significant impact. Nevertheless, the regression discontinuity design robustly confirms that it is possible for accelerator programmes to have a significant positive impact on the startups that they support.

Because this method could not be extended to a broader set of programmes, we used data from a survey of startups that had participated in any UK accelerators or incubator to determine how such programmes add value to startups (i.e. which types of support make the biggest difference to startup success and by what mechanisms). Answering these questions for the general case is complicated by the variety of programmes, offering a wide range of support services and with a broad range of objectives, which are difficult to neatly distil into a small number of archetypes. Moreover, the pathways to impact are many, both direct and indirect. However, by looking at a relatively broad sample of startups and different programmes, we attempted to identify and analyse common factors – albeit less robustly than with the narrower regression discontinuity design.

Our broader study finds that most types of support are positively associated with at least one outcome measure, but that few interventions could be positively linked with multiple outcomes. This reinforces that programmes need to prioritise their goals and tailor their design to desired outcomes. For example, a programme focussed on employment growth will likely require different interventions than one focussed on improving R&D intensity in startups.

Drilling into specific factors, in this broader study we found evidence that (i) direct funding through a programme and (ii) help with team formation both had a positive relationship with several outcome measures. These results complement those from the regression discontinuity design on the positive impact of the provision of non-monetary services on startup performance. In our view, these types of support are thus most likely to contribute to startup success.

We also found evidence in support of the existing literature (e.g. Schwartz 2013; Yu 2018) suggesting that incubators and accelerators help startups evaluate their business models, which leads to slower (more cautious) growth and a higher failure rate for incubated and accelerated startups that received help in developing their business model. In our results, startups that receive help in testing and refining their business model rate the programme's impact more highly and, at the same time, show slower growth and a diminished likelihood of receiving additional funding. As suggested earlier, this may be beneficial since helping poor ideas to fail faster ultimately improves the efficient allocation of resources. It also underscores why business survival rates alone should be interpreted cautiously as a success metric for a programme.

Perhaps surprisingly, we found no evidence for the provision of office space, lab space or equipment having an impact on startup outcomes. While it is possible that physical space is required to ensure interaction of peers, anecdotal evidence from startups' comments at our roundtable events indicate that many founders prefer to work at home than in an accelerator or incubator space. This raises the question about whether the support types for which we did find a positive impact might be provided more cost-effectively via remote, 'virtual' programmes. Such virtual programmes may also have the benefit of helping new businesses in areas of the country which currently have less physical support infrastructure – although they may not deliver the same ecosystem benefits.

In terms of spillovers and wider ecosystem impact, we found that accelerators can have a positive impact in attracting investment to non-accelerated as well as accelerated firms – although further work may be needed to understand the precise mechanisms that are driving this increase in investment, and whether this is genuinely additional or displacement from adjacent regions. (Additionally, since many spillovers seem to arise from physical proximity, it seems possible that 'virtual' accelerators might be more cost-effective in supporting individual startups, but much less effective in delivering wider ecosystem benefit). Due to a lack of suitable data, we were regrettably unable to offer a similar conclusion for incubators, so further research is also needed to clarify whether such an 'investment attraction effect' exists for incubators, as well as the potential of all programme types in creating other (non-investment) spillovers.

4.2 Limitations of the study

A significant limitation in this study was that, due to a paucity of (or for some analyses, complete lack of) data on incubators and their participants, we were unable to robustly compare differences in the impact of incubators to that of accelerators. While accelerators and incubators offer similar types of support, the time spans over which support is delivered is typically quite different, the average time spent in an incubator is around 2 years, compared to around 6 months for an accelerator. Since incubators typically provide support less intensively but over longer periods of time than accelerators, it may be the case that certain types of support may be more – or less – effective in this context.

Similarly, while some types of startup may benefit more from support given over a short but intense period others may be more suited to support being provided over a longer time period. Indeed, responses to open-ended questions in our startup survey provided some evidence that startups often desire a more long-term view of their development than is currently possible in the programmes in which they participated. The stronger emphasis on long-term development provided by incubators may therefore be a better fit for some types of business.

A related limitation of our data is that we were unable to explore how long the positive impacts of attending a programme last for, i.e. we did not compare the short-term versus the longer-term effects of participation. For example, in our RDD analysis exploring the impact of one corporate accelerator, all startups had applied to the accelerator within the last 5 years but we did not have a large enough data sample to differentiate the impact experienced by those that applied 1 year ago from those that applied 5 years ago.

We faced a similar problem when using our startup survey data to explore the relative impact of different types of support. In this case we experienced the added issue that although we know approximately when startups in our sample joined an accelerator or incubator, we do not know how long they took part in the programme for (i.e. when they graduated), so we cannot tell how long they received support for and also how long it has been since they stopped receiving support. In order to answer this question, future work could follow the progression of a panel of startups from the time they apply to a programme until a few years after they graduate allowing a more in-depth longitudinal analysis.

Concerning other limitations of the study and opportunities for further research, we have not examined the cost-effectiveness of accelerators and incubators, return on investment or the sustainability of the business models of incubation programmes – nor compared these with other potential forms of startup support. The study which preceded this report (Bone et al. 2017) discussed growing concerns about the financial sustainability of programmes, especially in view of often unclear goals and success metrics. This research does not allay those concerns.

A further limitation of the research is that our modelling of different types of incubation support did not account for possible self-selection (sorting) effects. If startups self-select into certain types of accelerators based on their own needs and the accelerator’s characteristics (e.g. types of support offered), this may lead to biased results. In our experience this is not the case; entrepreneurs typically based their choice on a variety of factors including overall quality, location, and sector verticals. However, we would expect selection effects to become more pronounced as entrepreneurs’ understanding of programmes’ fit with their needs becomes more sophisticated, perhaps aided by tools to allow startups to identify their own weaknesses and to compare the differences between programmes. Further research should therefore bear this in mind.

An additional limitation of the study is that, whilst the regression discontinuity design helped eliminate the problem of the selection effect, it was not possible to disentangle how much of the positive impact we found was due to signalling (certification) effects. We recommend that future work tries to understand the importance of this (though we acknowledge that this is not simple: even within education, where the datasets are vastly richer, the role of signalling remains much disputed).

This study mirrors past work in finding that the optimum design of a programme is likely to be highly context-dependent (such as in terms of size, sector and location of the startup). Given that this is so, it is understandable that there may be doubts about whether the evidence of impact from incubation programmes elsewhere can be applied to programmes in the UK context. However, this study adds to the growing evidence base that incubators and accelerators can have a positive impact, not only on the startups they support but also on the wider ecosystem in which they are situated.

4.3 Recommendations

4.3.1 For public funders

Invest in pilot programmes and further research to understand good practice, displacement effect (including any other ecosystem effects), and longevity of impact

The evidence for the effectiveness of incubators and accelerators suggests that they could be a useful tool for driving regional economic development. The evidence for spillover benefits of accelerators (into non-participating startups) provided by this study strengthens the policy argument in favour of public support. However, we suggest that, before committing long-term funding into such programmes, public funders should invest in further research to understand good practice, the extent to which ecosystem-level benefits might be the result of displacement from neighbouring areas, and the time span over which incubators and accelerators have a positive impact. This research could follow an experimental approach, investing in and evaluating pilot programmes.[48]

Continue to investigate other types of intervention alongside incubators and accelerators

Whilst this study suggests that incubators and accelerators can be part of a toolbox of possible interventions which aim to boost innovation and entrepreneurship, it does not evaluate the relative cost-effectiveness of different interventions. Therefore, we do not know whether investing in these programmes is the most efficient use of public money or how this type of support compares with other potential interventions, such as tax credits, direct grants or network building. We suggest that public funders should continue to investigate other types of support alongside incubators and accelerators in order to understand their relative cost-effectiveness.

Make data-sharing obligatory for incubators and accelerators receiving public funding

The lack of publicly-reported data on startup outcomes from accelerators and incubators was a significant inhibitor for this study, as it has been for other research in this field. It is the authors' view that more could be done to encourage incubators and accelerators to share data and to report outcomes. This is especially true if the programmes concerned are in receipt of public funding, in which case we suggest that making such data available should be an essential criteria for programmes receiving funds. Though we acknowledge that this may be difficult to enforce.

[48] See Nesta and it's Innovation Growth Labs's (IGL) work on for more information about experimentation: https://www.nesta.org.uk/feature/innovation-methods/experiments-and-trials/

4.3.2 For programmes

Assess your own impact or share data with researchers to do it for you and use data-driven insights to optimise your programme design

It is clear from this and other studies that not all programmes are equal and that offering certain types of support has a larger impact than others. However, there is still a lot of uncertainty around the effect of sector, location and other factors on optimum programme design. Incubators and accelerators could do more to assess their own impact and test what programme designs work best in their context. If they do not have the capacity to conduct these analyse in house, there are many academic and think tank researchers in the UK which would be eager to conduct research in partnership with programmes if given access to their data. Assessing the impact of your programme can help you demonstrate your value to funders as well as help you optimise the design of your programme to maximise your effectiveness.

4.3.3 For Local Enterprise Partnerships

Understand how incubators and accelerators can be part of your Local Industrial Strategy and connect with other LEPs in order to share experiences and best practices

While our research has found that some LEPs are already including incubators and accelerators in their Local Industrial Strategies, we would encourage LEPs which are not already doing so to also consider the potential value of including incubators and accelerators. LEPs that we spoke to also reported a strong desire to connect with other LEPs in order to share experiences and best practices in working with incubators and accelerators. We believe that there is a role that pre-existing networks working in this space (e.g. The LEP Network or The Centre for Entrepreneurs Incubator and Accelerator Network) to coordinate such networking and knowledge sharing opportunities.

5. Appendices

Appendix 5.1 Extended Literature review

5.5.1 Impact on overall outcomes of participating startups

Impact of accelerators

Beginning with studies that specifically explore the impact of incubators on participating startups, in the fluid space of support structures for technology firms, one of the early studies investigates science parks in the UK that were established with government help in collaboration with universities mainly in the 1970s and 1980s in an effort to encourage R&D and innovation in small and medium-sized firms. A 1997 study by Westhead compares on-park and off-park firms and finds no statistically detectable effect of science parks on input or output measures of innovation, including R&D expenditures, percentage of qualified scientists and engineers, innovation diffusion and the survival of tenant firms (Westhead 1997). Westhead and co-authors later reviewed the developing literature on science parks and concluded that the returns to being located in a science park seem negligible (Siegel, Westhead, and Wright 2003). They speculate that imprecise estimates may be due to differences in the types of science parks, their ownership and the types of services provided to firms.

Colombo and Delmastro (2002a) compared a group of new technology based firms that had resided in an Italian incubator to a matched control group of similar firms that had not participated in an incubator. They found evidence suggesting that the incubator had a positive impact on employee growth but no effect on innovation, as measured by R&D intensity.[49] A possible shortcoming of this study is that it only considered surviving firms and therefore failed to account for how survival affects growth rates.

Schwartz (2013) compared the survival rates of residents of five German incubators to a control group of similar but non-incubated business. They found that for three of the five incubators, participating firms were actually less likely to survive for ten or more years than those in the control group. The other two incubators had no significant effect on firm survival. While decreasing survival rates may appear to suggest that these incubators have a negative impact on the startups they support, this may not necessarily be the case. Rather, it may indicate that these incubators help firms understand the viability (or unviability) of their idea, resulting in them killing bad business ideas sooner than they otherwise would; and thus preventing time and money being wasted on businesses that were doomed from the get-go.

Effects on survival extend beyond the time that firms spend at incubators. On graduation from an incubator, firms experience an elevated risk of closure that lasts up to 3 years after leaving the incubator (Schwartz 2009). It may be interpreted as an indication of the positive effects of incubator support if the discontinuation of low rents, shared facilities, management support or access to business networks has an immediate negative effect on subsequent survivability. Equally, however, it may suggest that such programmes can end up serving as ‘life support’ for firms, which is almost never the desired policy goal.

While the method of matching similar incubated firms with non-incubated firms – as used by Schwartz (2013) and Colombo and Delmastro (2002) – attempts to take into account the selectivity of incubators, it is not clear whether the characteristics used to conduct this

[49] Measured by the ratio of R&D expenses to sales, of tenant firms.

matching adequately represent those that contribute to firm success in the selection process. Colombo and Delmastro (2002), for example, use firms' location, industry, age, and legal form to perform matching of firms but later find evidence that incubators attract firms with better-than-average human capital, as measured by educational attainments and prior working experience. It may therefore be the better human capital of incubated firms that causes any observed differences between incubated and non-incubated firms.

Another method that has been used to test the effect of incubators is to look at the effect the amount of time spent in an incubator has on outcomes for firms. Rothaermel and Thursby (2005b) asked this question of firms attending the Georgia Institute of Technology incubator in the US. The authors found that the length of time spent in the incubator had a positive effect on firm survival but a negative impact on the probability of them graduating from the incubator. Here graduating means that the startup leaves the incubator and operates as a stand-alone going concern or is acquired. This suggests that while the incubator may have protected firms from failure, it simultaneously prevented them from growing or developing much further.

A related paper by the same authors also found that firms that remain longer within an incubator may be less likely to raise VC funds but more likely to generate significantly higher revenues (Rothaermel and Thursby 2005a). This illustrates some of the tensions that are apparent, and the need to define success criteria before one can determine performance.

Impact of accelerators

The evidence for the impact of accelerators is a little stronger than that for incubators. One way in which researchers have tried to assess the impact of accelerators is simply to ask participating startups. In order to understand how much value accelerated startups think accelerators added to their business, Christensen (2014) asked 51 accelerated startups "If the accelerator provided no funding to your company at all, how much equity would you give them just to go through the program?" While 21% of the startups reported they would allocate no equity, suggesting they saw no value in the accelerator they attended, 55% reported they would allocate between 1% and 6% equity, even without funding, implying that in general participating startups believe that accelerators are adding value in excess of the funding they give.

Using a more quantitative methodology, Roberts et al. (2016) compared the performance changes of firms that participated in one of fifteen accelerators around the world[50] to firms that applied to but were rejected from these programmes. Comparing firms accepted by the programme to rejected ones allows the authors to control for the effect of self-selection by firms into a programme (i.e., the decision to apply) but does not control for the selectivity of the accelerator programmes. They found that accelerated firms had higher revenue growth and investment growth, but that there was no effect on employee growth.

Hallen et al. (2016), at least partially take into account the effect of accelerator selectivity by comparing a sample of US-based accelerator participants with those "almost accepted" to the same cohorts. The authors found that most of the studied accelerators had a positive impact on the speed with which firms raised funds or gained customer traction (as measured by web traffic). A smaller number of accelerators increased the speed of startups being acquired. It is worth noting that the five accelerators involved in this study were all 'top tier' accelerators, and so it is not clear whether these findings can be generalised to the entire accelerator population.

[50] Accelerators were all run by Village Capital and were based in the U.S, India, Mexico, South Africa, Netherlands and Kenya.

In a study assessing the impact of the Startup Chile accelerator, Gonzalez-Uribe and Leatherbee (2016) showed that the programme's entrepreneurship school (which includes several services other than business instruction, such as increased visibility) affects employment and scale, whereas the basic services of funding and coworking space on their own have no apparent effect on venture performance. To assess the impact of the basic services (entrepreneurship school), the authors compare the performance of the Startup Chile (school) participants with that of rejected applicants. They robustly take into account the accelerator's selectivity in both sorting participants to the accelerator and to the entrepreneurship school, by controlling for differences in quality among applicants using the numerical scores given to firms by judges when applying to the accelerator and when applying to the entrepreneurship school, and by exploiting the programmes' predetermined, fixed capacity threshold to the general programme and fixed quality threshold to the school.

When comparing the outcomes of participants of two top US accelerators to a matched group of angel-funded counterparts, Smith and Hannigan (2015) found that accelerated firms have lower survival rates than angel-funded firms, mirroring what Schwartz (2013) found for incubators. However, they also found that accelerated firms are more likely to be acquired than their non-accelerated counterparts. This suggests that accelerators can help bad ideas or businesses "fail faster", while helping better ideas to find investment. Smith & Hannigan (2015) put this down to the existence of 'demo days', suggesting that while these give startups the opportunity to pitch to investors, if they do not manage to obtain investment on this day, their likelihood of failure is high.

Similarly, Yu (2016) finds that firms that have been through an accelerator raise less money and have lower survival rates than a matched group of non-accelerated firms. Yu (2016) proposes that this is a result of entrepreneurs with the best ideas not applying for accelerators as they do not want to dilute their equity. Rather, accelerators, she argues, attract startups that are less certain about the viability of their idea and that the intense feedback that participants receive from accelerator staff, mentors and other participating startups helps them to more accurately assess their viability. As discussed above, this indicates that accelerators can help bad ideas fail faster.

Alongside studies that have specifically tested the impact of incubators or accelerators impact, several have conflated the two models.[51] Lasrado et al. (2016), for example, found that firms that have been through an incubator or accelerator have more employees and sales revenue than firms that have not participated in a programme.[52] In addition, the study finds that university affiliated programmes are associated with faster sales and job growth than those not connected to a university. Conversely, another study by Amezcua (2010) also looked at the effect of whether or not incubators and accelerators are affiliated with a university, and finds that while university affiliation has a positive effect on firm survival, it has no effect on employment or revenue growth of participating firms.

5.5.2 The effect of programme design on impact

At the level of an incubator's overall mission, some effects have been observed on the rate of survival of tenant firms in European incubators. If an incubator's self-declared purpose includes "stimulating entrepreneurial spirit" or "supporting SMEs", its tenant failure rate during the firms' stay at the incubator decreases (Aerts et al. 2007). By contrast, mission statements including

[51] Conflated according to our working definitions, but definitions in the literature are diverse and sometimes overlap.

[52] Stokan et al. 2015 also finds that accelerated or incubated firms have more employees than firms that have not been through a programme

"contributing to competitiveness of local economy" and "supporting specific sectors" have no effect on tenant survival.

Employment growth in relation to incubator support was studied by Pena (2004) in a sample of 114 startups that all attended the same incubator programme in the Basque Country. Business education programmes and assistance services collectively improved employment in startups, whereas the effects of savings (from the use of subsidised space and equipment), networking and exchange activities with other tenants and external contacts facilitated by incubator (e.g., investors, local authorities) remained statistically negligible. None of the support services studied had a detectable effect on profits or sales.

Hallen et al. (2014) suggested that the increased speed with which firms raised funds or gained customer traction which they observed in incubated and accelerated firms may be explained by what they describe as "broad, intense, and paced (BIP) consultation". They describe BIP as knowledge sharing that relies on the direct sharing of experiences which are then translated to the startup's own situation. They suggest that in incubators and accelerators BIP consultation takes place through mentoring with domain experts, interviews with customers, private meetings with programme directors, weekly check-ins with other participating startups, and discussions with seminar speakers.

These hypothesised effects of non-monetary services receive some support in a study by Gonzalez-Uribe and Leatherbee (2016). They test the effect of startups receiving entrepreneurship schooling on top of the basic support package (cash and coworking space) offered by the Startup Chile accelerator and found that schooled startups appeared to hire more and grow their customer base faster than non-mentored participants.

In a study further focusing on the potential impact of non-monetary services of accelerators, Gonzalez-Uribe and Reyes (2019) exploit the random assignment of applicants to application judges with different tendencies to award high scores. They find that the entrepreneurship schooling provided by the ValleE ecosystem accelerator in Colombia (in the form of bootcamps, mentoring and visibility) impacts revenue, employment and profits, even though the accelerator provides no funding. Gonzalez-Uribe et al. (2018) find similar results for one of the largest corporate accelerators worldwide, which provides no seed funding, but provides participants with business training, advice and access to the corporate sponsor's servers and software.

The optimum programme design appears to depend on how competitive the environment is in which the programme is active. Amezcua et al. (2013) find that for firms operating in a competitive business environment,[53] participating in an incubator or accelerator that offers networking and management training produces firms with higher survival rates; however, for those working in less competitive environments networking appears to have a negative effect on survival and management training has no effect on survival. This suggests that management training and networking — by facilitating exchanges of resources, knowledge or more formal collaboration — can give firms a competitive advantage. This same study found that for startups operating in a non-competitive environment, attending a programme that focuses on supporting startups from a particular sector leads to a higher likelihood of survival in comparison to attending a non-specialised programme; however, the opposite was true for startups operating in a more competitive environment. A potential explanation for this is that as a sector becomes denser, competition over funding and customers begins to outweigh the

[53] As measured by the number of organisations in the same sector at the county level in the organisation's founding year.

increased level of knowledge and resource sharing, and collaboration opportunities that come with working alongside other business in the same sector as yourself.

Even when asking startups directly about which types of support they value the most the results are mixed. When asked, startups reported finding mentoring, coaching and feedback alongside network, alumni and prestige to be the most valuable aspect of the accelerator programme they attended (Christiansen 2014). The same startups reported finding direct investment from the accelerator and connections to investors to be less useful. However, another study that asked a similar question found that while networking opportunities were highly valued by startups, access to funding (direct and indirect) was also highly valued but skills development, awareness and credibility and gaining access to a group of like-minded entrepreneurs was not seen to be as useful Roberts et al. (2016).

5.5.3 The effect of incubators and accelerators on the broader business ecosystem

Anecdotally, incubators and accelerators often serve as ‘focal points’ for an ecosystem, providing not only a degree of deliberate coordination but also a geographic locus which increases the chance of serendipitous interactions. Do studies support this notion?

One study commissioned by BEIS looked into the outcomes for businesses located in incubators as well as those located within the areas surrounding incubators (Department for Business, Energy and Industrial Strategy 2019). This study had a particular focus on understanding whether the presence of incubators or science parks might displace economic activity from their surrounding areas. The authors found that being located on an incubator site was associated with increased employee growth, turnover growth and productivity growth[54] and that there was no observed displacement effect for the surrounding area. Furthermore, it was found that the presence of an incubator was associated with increased growth in normalised wages (i.e. average of wages relative to average wages in a specific sector and occupation) within two to three kilometres around incubator sites and increased high level occupational change up to four kilometres around incubator sites. Taken together, these results suggest that incubators can help promote the creation of high-quality jobs in their wider ecosystem (Department for Business, Energy and Industrial Strategy 2019).

Accelerators may also affect the availability of finance in a region. In their study of US census regions, Fehder and Hochberg (2014) tested the effect of the launch of an accelerator on the availability of venture capital funding in the region that the accelerator is located. They found that the launch of an accelerator was associated with an increase in the number of VC deals and the total amount invested in the region. Importantly, much of the increase in funding events involved non-accelerated companies. This suggests that by attracting VCs with activities such as mentorship and demo days, accelerators simultaneously increase the exposure of non-accelerated firms nearby.

[54] As measured by the number of organisations in the same sector at the county level in the organisation's founding year.

Appendix 5.2 Focus group agenda / topic guides

5.5.1 Focus group with incubators / accelerator managers

Introduction to the roundtable and our research - Jonathan Bone / Chris Haley (10 minutes)

Introductions around the table (2 minute each; 20 mins max)

Participants introduce themselves, their accelerator/incubator and tell us what their accelerators/incubators goals are, and how they support startups

Selection of startups (10 minutes)

What do you look for in the startups you choose?

What is the application process?

Do you score startups that apply in a consistent way?

Are you able to share data on startups that were accepted / not-accepted and the score you gave them?

Accelerator/incubator impact (10 minutes)

What would success look like to you?

Large exits, increased jobs in your region, change in attitudes towards entrepreneurship, better links between startups and academia etc.

What do you do to measure the impact of your accelerator?

What measurements do you use, do you have a control group etc.

If you don’t look at impact, so you collect data on startups for other reasons?

Environmental constraints (10 minutes)

What barriers to achieving greater impact on startups do you encounter (e.g. not enough applicants, finance, skilled people, uncertain market demand, etc.)?

How do you interact with other elements of your ecosystem? (10 minutes)

How do you think this benefits your incubator/accelerator and the startups you support?

What challenges do you face in working together? (e.g. do you compete? is there duplication of efforts?)

Government support (10 minutes)

Are you publicly funded?

What support, if any, does your incubator/accelerator get from government?

Feedback on Survey design (give them 10 minutes to look at questions; then 15 minutes to give feedback)

Do the options we give as answers make sense, should we add any?

Is there and questions that should be reworded / removed

Should we add anything?

What would incentivise you to take the survey / provide data? Is it enough that the report will give you a benchmark?

Anything else people would like to discuss (10 minutes)

Debrief and thank you (5 minutes)

5.5.2 Focus group with incubator / accelerator participant firms

Introduction to the roundtable and our research - Jonathan Bone / Chris Haley (10 minutes)

Introductions around the table (2 minute each; 20 mins max)

Participants introduce themselves, their startup, the incubator/accelerator they participated in and why they wanted to join an incubator/accelerator

What made you decide to choose that incubator/accelerator over all the others? (10 minutes)

What barriers were you facing and how did the accelerator/incubator help you overcome these aspect of your experience? (10 minutes)

What was the most useful and least useful aspect of the incubator/accelerator you attended? (10 minutes)

Do you track your startups progress? (10 minutes)

What metrics do you use to assess your company? (e.g. Revenue growth, Investment, Customer traction etc.)

Is this data you would be willing to share?

What challenges do you face in measuring/tracking your progress?

Was there a noticeable increase in progress since being part of the programme?

Government support (10 mins)

Have you benefited from any government support (e.g. tax relief)?

What do you think the role of government should be in the startup ecosystem?

What other startup support have you received? (10 minutes)

Have you previously, or since being part of another incubator or accelerator

Have you used coworking spaces, received VC investment etc.?

How did the accelerator/incubator programme compare? (e.g. did the VC help you in other ways? Did you feel there was duplication of efforts etc.?)

Feedback on Survey design (give them 10 minutes to look at questions; then 15 minutes to give feedback)

Do the options we give as answers make sense, should we add any?

Is there and questions that should be reworded / removed

Should we add anything?

What would incentivise you to take the survey / provide data? Is it enough that the report will give you a benchmark?

Anything else people would like to discuss (10 minutes)

Debrief and thank you (5 minutes)

Appendix 5.3. Supplementary information on startup survey respondents

Most startups are currently active (424), while a minority is pre-formation (5), dormant (4), has ceased trading (5) or has been acquired (1). Founders own more than half of the shares in 86% the sample firms. About 36% of startups consider their enterprise to be a socially driven business - that is, one that exists primarily to achieve social or environmental objectives through enterprise and trading. Table A1 shows summary statistics for numeric variables collected in the survey.

Startups in our sample have a wide range of sizes and other characteristics. The typical startup does not have positive sales turnover or assets when joining an accelerator, but grows substantially and attracts investment in the following period. It is important to note here that we do not observe when startups exit accelerators, as many accelerators have alumni programmes or soft exits, which makes it difficult to define an exit event. For this reason, we observe the entire period since applying to an accelerator until today, but scale variables by the length of this period wherever appropriate.

Startups are clustered in the digital and health sectors, with 22% of startups reporting some business in either sector (see Table A2). Education and engineering/manufacturing are the mentioned by 13% and 11% of startups. Startups were allowed to choose any number of sectors to allow for businesses operating in multiple sectors. For the purpose of our quantitative analyses and in light of the relatively small sample size, we combine these sectors into eight categories: 24% of startups are in the agriculture/construction/transport/retail sector, 21% in professional services and research sector, 8% in public administration and services, 24% in manufacturing, 12% in arts, 31% in information and software, 13% in education, and 22% in the health sector.

Table A1: Descriptive statistics. The table below shows descriptive statistics for variables that were measured on a numerical scale. Most variables are measured for the year before joining an accelerator and for the most recent financial year. The number of patents is the number of patent applications since joining an accelerator. R&D is the amount of expenditures for research and development in the most recent financial year. Mentoring intensity is calculated from a numerical representation of survey responses: 0=None, 1=Less than 1 hour/week, 2=1-2 hours/week, 3=3-4 hours/week, 4=5-8 hours/week, 5=9-16 hours/week, 6=17+ hours/week.

	N	Min	Max	Mean	Median	SD
Patents (number)	408	0	21	0.4	0	1.5
R&D (£'000)	286	0	10,000	190.9	25	706.9
Employees before joining	299	0	243	3.6	1	14.8
Employees now	292	0	284	8.4	3	22.1
Employees with a degree (before joining)	291	0	243	3.3	1	14.7
Employees with a degree (today)	285	0	284	7.1	3	21.1
Sales (before joining, £'000)	275	0	34,600	199.9	0	2,106.0
Sales (today, £'000)	270	0	85,700	594.7	35	5,267.0
Pre-tax profit (before joining, £'000)	248	-4,000	10,600	15.5	0	727.8
Pre-tax profit (today, £'000)	243	-5,000	35,800	56.5	0	2,355.7
Total assets (before joining, £'000)	240	0	2,000	49.4	0	198.6
Total assets (today, £'000)	233	0	5,000	189.8	5978	587.1
Investment (before joining, £'000)	267	0	366,300	1530.7	0	22,423.0
Investment (total to date, £'000)	267	0	443,300	22349.8	50000	27,152.6
Mentoring intensity	242	0	6	1.9	2	1.4

Table A2: Sector distribution. Enterprises were asked to select all sectors that apply to their business. 222 enterprises said they operate in exactly one sector, 112 operate in two sectors, 58 operate in three sectors, and 49 operate in more than 3 sectors. N=441.

Industry sector	Frequency	Percentage
Agritech	22	5%
Civtech / Public Sector Innovation	11	2%
Cleantech/Energy and the Environment	45	10%
Construction	9	2%
Creative Industries and Design	38	9%
Cyber Security	12	3%
Digital (including generalist AI & generalist blockchain)	97	22%
Education	57	13%
Engineering and Manufacturing	50	11%
Extractive industries (mining, oil & gas, fishing, forestry)	6	1%
Fintech (including insurance tech)	37	8%
Food	35	8%
Health and Wellbeing	96	22%
Internet of Things (IoT)	46	10%
Leisure	19	4%
Life Sciences	26	6%
Marketing technology	29	7%
Retail and e-commerce	57	13%
Smart Cities	30	7%
Space and Satellite Technology	11	2%
Telecommunication	6	1%
Transport	21	5%
Other	94	21%

Appendix 5.4. Supplementary information on sample used for analysis of corporate accelerator's impact

The average firm in the sample has 4.58 employees, 1.11 founders, is less than one year in age, is 46% likely to have raised outside financing, and has raised an average of $150,000 USD in outside financing at the time of application. Relative to applicants of ecosystem accelerators worldwide, as summarised by Gonzalez-Uribe and Leatherbee (2016) using data from the Emory Database, the businesses applying to the corporate accelerator appear younger, bigger and more developed as measured by previous fundraising.

The distribution of application scores is not continuous: rounded scores are disproportionately more prevalent (see Figure A1 for application score histograms). The prevalence of ties is a consequence of the scoring approach, which is based on open discussion and agreement by staff about projects' prospects, which naturally leads the group to classify applicants into round scores (as opposed to independent scoring of applicants across staff members, and with multiple criteria, as in other settings, which leads to more continuous score distributions; see Gonzalez-Uribe and Reyes, 2019).

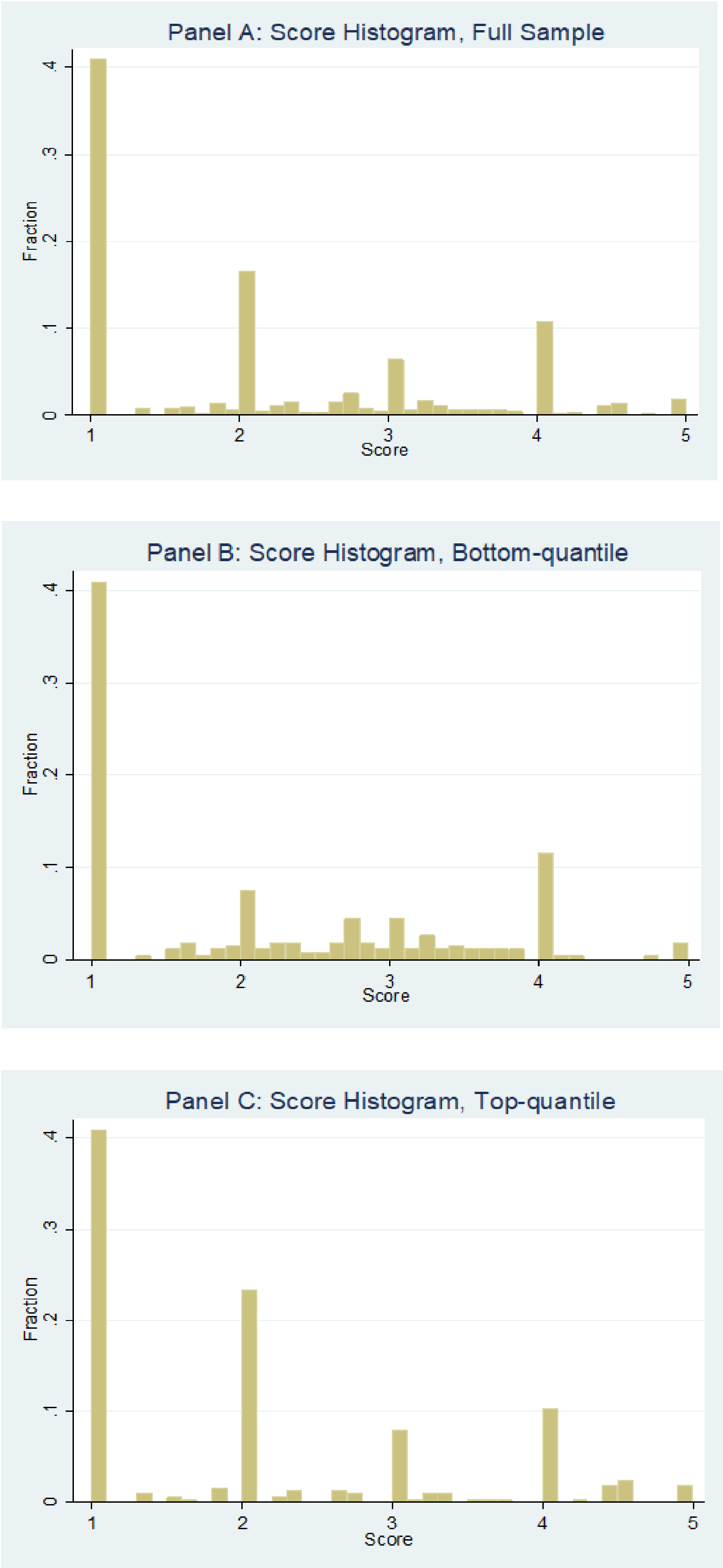
Table A3: Sample composition for analysis of corporate accelerator on participating startups. The table describes the sample composition by cohort. The data also includes information on post-application performance within 5 years of application to the accelerator, hand-collected by the authors using online searches in LinkedIn and Crunchbase. LinkedIn in one of the most common tools to recruit new hires among young, high-tech firms. Crunchbase is the most popular public site collecting information about funding rounds for young, high-tech firms.

	Applicants	**Participants**	**Companies in Top-20**	**Participants in Top-20**	**P(Acceleration)**	**P(Acceleration/Top20)**	**Average Score**	**Standard Deviation of Score**
Cohort 1	41	6	22	5	0.15	0.23	3.34	1.14
Cohort 2	201	9	37	9	0.05	0.24	1.88	1.2
Cohort 3	130	4	23	4	0.03	0.17	1.38	0.97
Cohort 4	98	7	20	6	0.07	0.3	2.76	0.71
Cohort 5	168	10	25	9	0.06	0.36	2.36	1.14
Total	638	36	127	33	0.06	0.26	2.13	1.19

Table A4: Summary Statistics for analysis of corporate accelerator on participating startups. The table presents summary statistics of the main variables used in the analysis.

Variables	Observations	Mean	Std. Dev.	Min	Max
Average Score	638	2.13	1.19	1	5
Z	638	6.76	9.32	-13	46
Acceleration	638	0.06	0.23	0	1
Number of employees	638	4.58	4.14	0	45
Number of founders	638	1.11	1.33	0	7
Company age	638	0.86	1.54	0	14
Value fundraising	638	150,565	663,432	0	10,900,000
Outside Financing	638	0.46	0.5	0	1
Family and friends	638	0.08	0.27	0	1
Grant	638	0.06	0.24	0	1
Business angels	638	0.08	0.27	0	1
Venture Capital	638	0.03	0.16	0	1
Online presence	638	0.8	0.4	0	1
Change in employees	638	-0.25	1.07	-3	5
Change in fundraising	638	306,831	2,250,943	-10,900,000	36,000,000

Figure A1: Distribution of Application Scores. The figure plots the histogram of application scores across 0.1 bins. Panel B (C) use the sub-sample of applicants in London cohorts with ties below (above) the median number of ties across cohorts:



Appendix 5.5. Supplementary methodology for analysis of corporate accelerator on participating startups

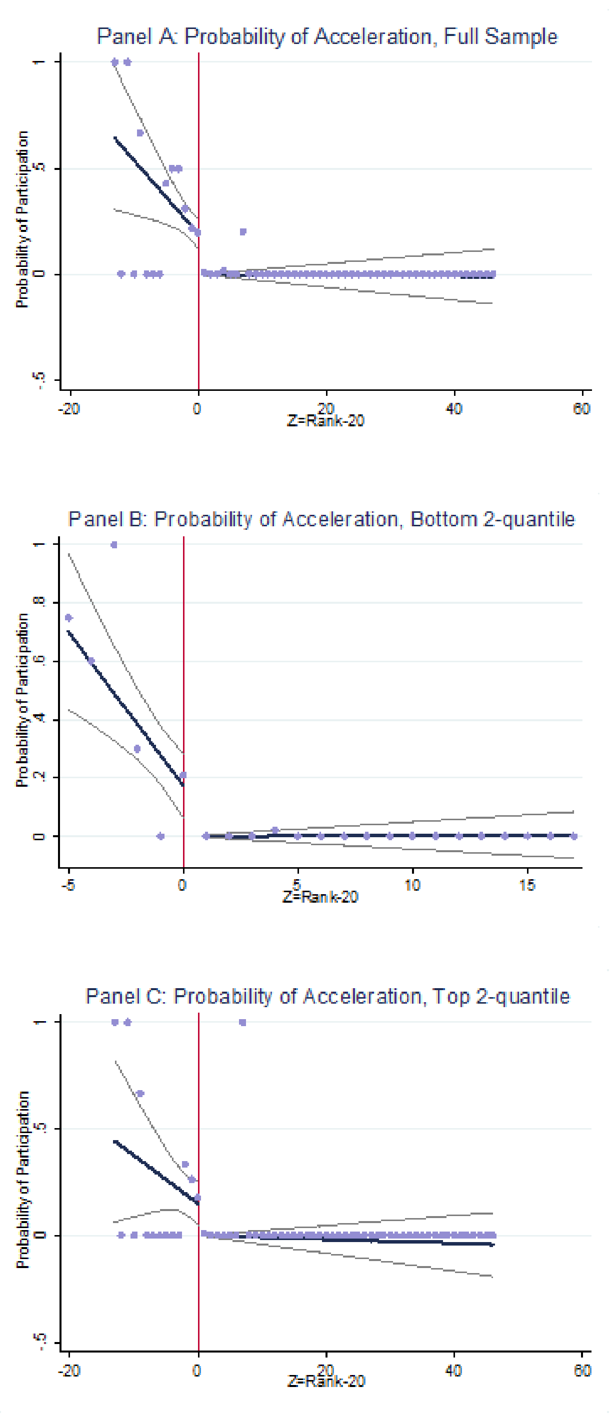
5.5.1 Discontinuity of Acceleration at the Interview Threshold

In this Section we first show evidence of discontinuity of acceleration at the interview threshold. We then present evidence against the empirical relevance of potential manipulation of ranks around the threshold.

The discontinuity in acceleration at the interview threshold is visible in Figure A2 of this appendix. We plot the fraction of participating applicants against the normalized rank (i.e., the ranking of the startup minus 20) calculated across bins of 1 rank and plotted in dots. Because we plot acceleration against normalized ranking, higher ranking companies are represented to the left of the interview threshold, which corresponds to the 0 in the x-axis.

Figure A2 below plots the probability of acceleration against normalized rank based on estimates of equation (1). Panel B (C) use the sub-sample of applicants in London cohorts with top-20 ties below (above) the median number of top-20 ties across cohorts. The solid line depicts the coefficients estimates and the dashed line the 95th confidence interval. The dots correspond to simple average probability of acceleration for bins of size 1 of normalized score.

Figure A2: Probability of Acceleration and Normalized Ranking



We estimate the size of the discontinuity using the following equation:

$$(1)\ acceleration_i = \beta * Top20_i + f(Z_i) + f'(Z_i) * Top20 + \gamma X_i + cohortFE + \varepsilon_i$$

where i indexes startups, acceleration indicates whether the applicant participated in the corporate accelerator and Top20i is a dummy that equals 1 if the applicant ranked higher than the interview threshold (i.e., among the top 20 companies). f(Zi) and f'(Zi) are low-degree polynomials on the normalized rank Z (i.e., the rank of the company minus 20), that include interactions with 2-quantiles of number of applicants that tie at the 20-th rank (i.e., the variable

High indicates observations in cohorts at the top 2-quantile of number of companies tied at the 20-th rank). The use of low-degree polynomials that can differ on either side of the threshold is standard in the literature: (Gelman and Imbens 2017) warn against estimation noise from using global high-order polynomials. The inclusion of interactions of 2-quantiles of score ties is more novel, but necessary, given the prevalence of score ties in the sample (see Table A5 and Figure A2).

An important data limitation is the normalized ranking discreteness. (Lee and Card 2008) note that discrete sorting variables can require greater extrapolation of the outcome's conditional expectation at the threshold as well as clustering observations at the level of the sorting variable, though the fundamental econometrics are not different. Thus, we present results clustering standard errors at the score level to control for heteroscedasticity across applicants with the same score. To determine the appropriate polynomial, we employ Lee and Card's (2008) goodness-of-fit test for RD with discrete covariates, which compares unrestricted and restricted regressions.[55] We cannot reject the null that the unrestricted regression does not provide a better fit using linear polynomials that are allowed to differ on each side of the threshold and include interactions with High¸ which is our main specification of equation 1 (see Column 7 in Table A5). Nevertheless, in what follows we also present results using other specifications of equation 1 for comparison.

The estimated discontinuity is sizable, significant and robust. Table A5 presents robust estimates of across different specifications of Equation (1), with varying polynomial degrees. The coefficient of Top20 in Column 7 implies that ranking higher than the interview threshold increases the probability of acceleration by 15.1% relative to other applicants in the same cohort. The coefficient on Top 20×High implies that the jump is not statistically different for applicants in cohorts among the top 2-quantile of score ties. The F-test of the excluded instruments (i.e., Top20 and Top 20×High) shows that the instruments are not weak: they exceed the rule of thumb of 10 (Stock et al. 2005).

[55] The unrestricted regression projects the acceleration indicator variable on indicator variables for each of the K ranks. The restricted regression is like equation (1). The goodness of fit statistic in the presence of non-normal homoscedastic errors is G≡(ESSR-ESSUR)/(ESSUR(N-K)), where ESS is the sum of squared errors, N is the number of observations, and J is the number of restricted parameters. G has a chi-squared distribution. The null hypothesis is that the unrestricted model does not provide a better fit. If G exceeds its critical value, we reject the null and turn to a higher order polynomial.

Table A5: Probability of Acceleration. The table presents estimates of different specification of equation (1). The standard errors are presented in parentheses and are adjusted for heteroscedasticity and clustered at the normalized rank level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

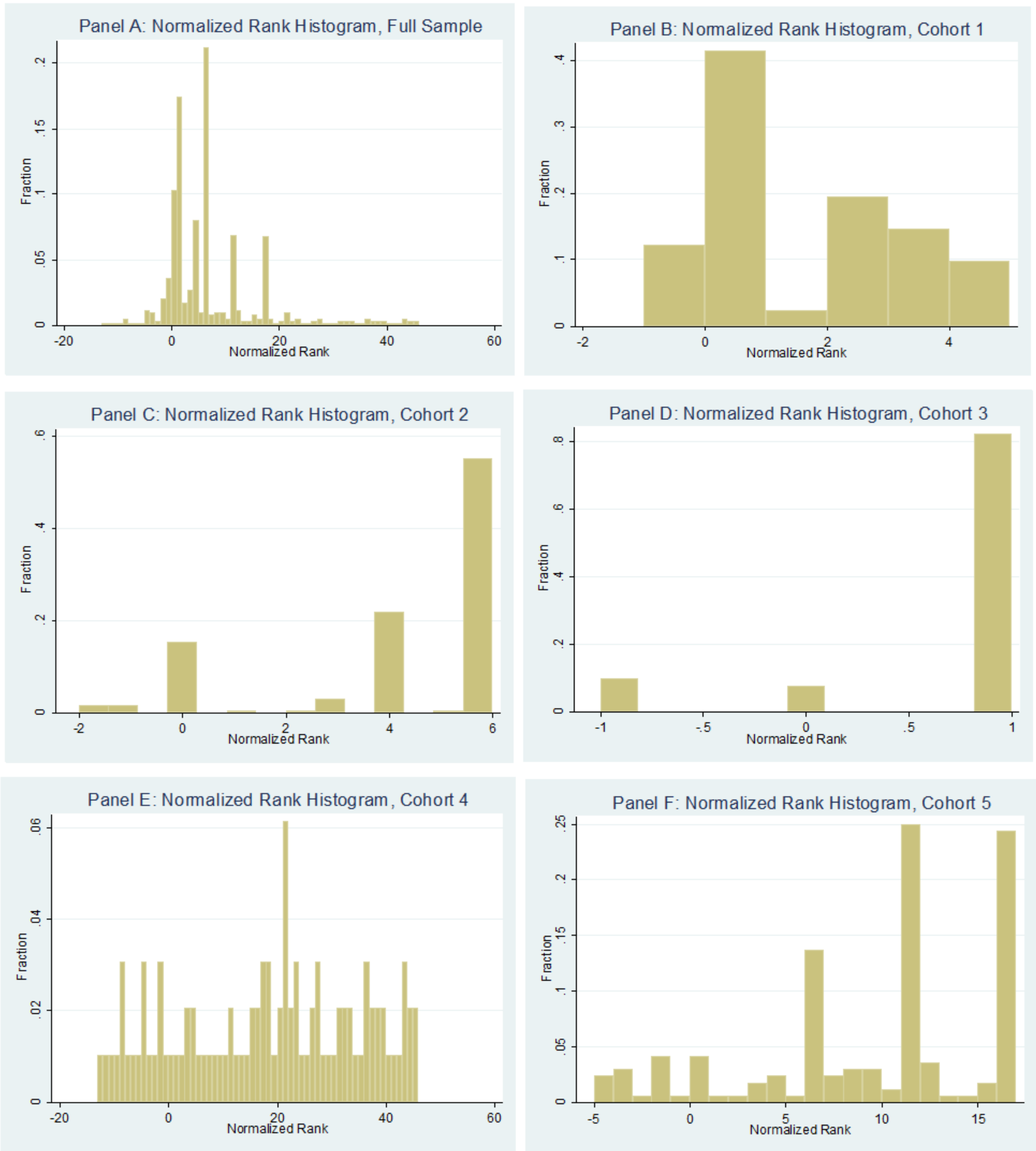
Dep. Var. Acceleration	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Top20	0.192***	0.169***	0.184***	0.150***	0.190**	0.199***	0.151***
	(0.044)	(0.049)	(0.047)	(0.048)	(0.080)	(0.067)	(0.047)
Top 20×High				0.025	-0.010	-0.007	0.017
				(0.080)	(0.107)	(0.086)	(0.070)
Z	-0.000	-0.004	-0.000	-0.001	-0.007	-0.002	-0.001
	(0.002)	(0.004)	(0.002)	(0.002)	(0.009)	(0.002)	(0.002)
Z×High				0.001	0.004	0.002	
				(0.004)	(0.014)	(0.004)	
Z×Top 20	-0.034**	-0.042	-0.049	-0.022	0.071	0.058	-0.022
	(0.017)	(0.045)	(0.044)	(0.018)	(0.048)	(0.042)	(0.018)
Z×Top 20×High				-0.084***	-0.076	-0.066	-0.081***
				(0.021)	(0.086)	(0.076)	(0.020)
Z2		0.000			0.000		
		(0.000)			(0.000)		
Z2× High					0.000		
					(0.000)		

Dep. Var. Acceleration	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Z2×Top 20		-0.001	-0.002		0.008*	0.007*	
		(0.004)	(0.004)		(0.004)	(0.004)	
Z2×Top 20×High					0.015	0.016	
					(0.013)	(0.013)	
Observations	638	638	638	638	638	638	638
R2	0.226	0.228	0.227	0.261	0.276	0.275	0.261
F All excluded instruments	18.77	11.99	15.32	40.88	24.56	94.01	60.88

We present three pieces of quantitative evidence against the empirical relevance of ranking manipulation around the threshold. First, in Figure A3 we show there is no obvious discontinuity in the distribution of normalized ranking at the interview threshold (i.e., normalized rank of 0): in fact, Panel A shows that the distribution is much more concentrated at a normalized rank of 1 (17.40%) and at a normalized rank of 6 (21.16%).[56] Consistent with the patterns in scores (Figure A2), the figure shows that the distribution of the normalized rank is not continuous, mainly due to the tendency of the scoring process to produce round scores. Panels B-F in the figure show large variation in the distribution of normalized rank across cohorts, pointing to the importance of controlling for the 2-quantiles of number of companies tied at the top 20 in the RD exercise.

[56] Unfortunately, the discreteness of the normalized rank prevents a McCrary density test, which is standard in RD applications exploiting continuous sorting variables.

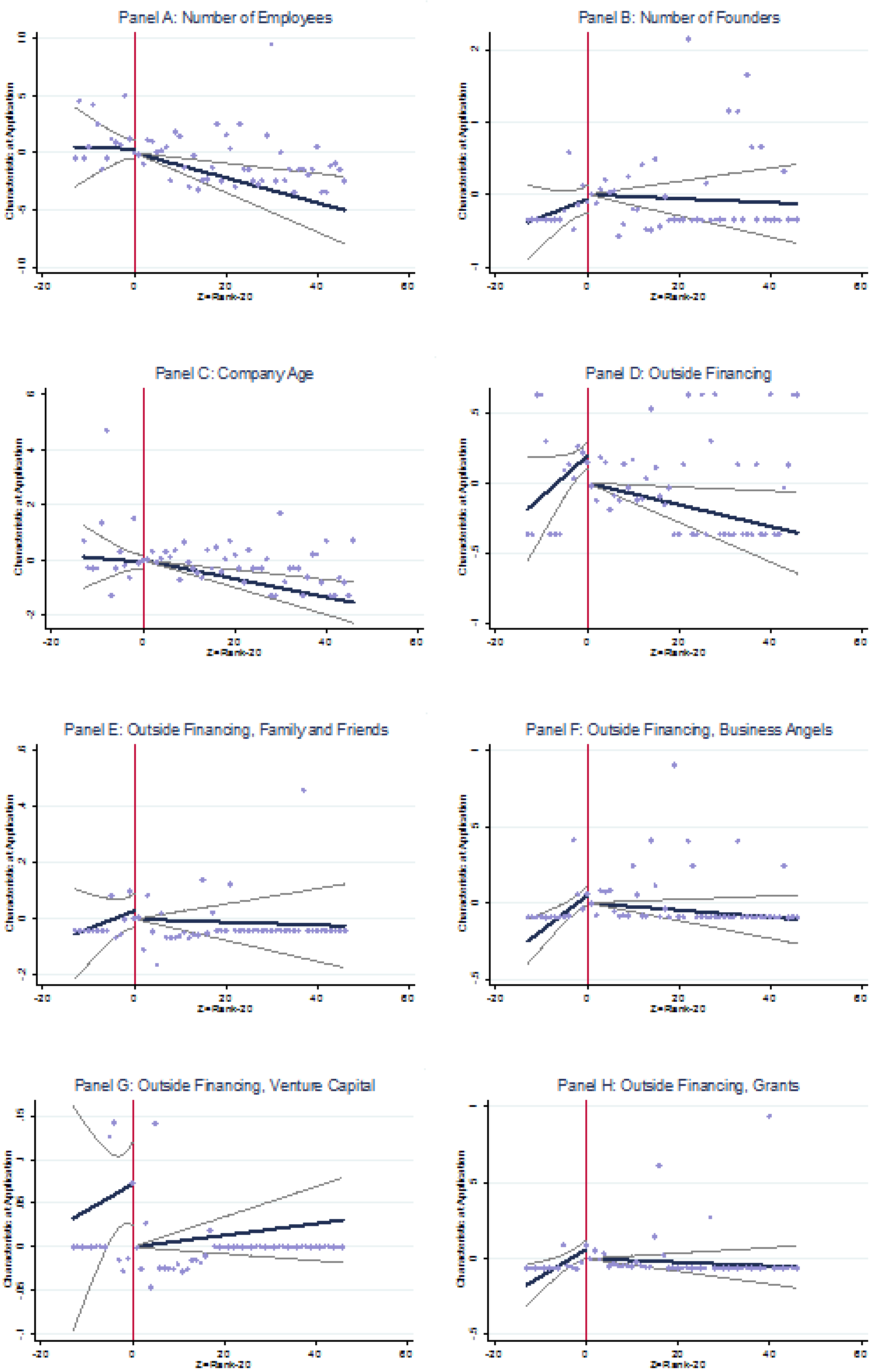
Figure A3: Distribution of Normalized Ranking (distribution of normalized ranks across cohorts)



Second, Figure A4 shows that companies ranking closely on either side of the threshold are very similar in characteristics measured at the application stage. We estimate different specifications of equation (1) using application characteristics (rather than acceleration) as dependent variables: to ease exposition, we present results based on linear polynomials that are allowed to differ on either side of the threshold, but that do not vary by 2-quantiles of companies tied at the top 20 position. In contrast to the probability of acceleration, for most applicants' characteristics we cannot reject the null hypothesis of no jump at the threshold. The only significant difference is for an indicator variable on outside financing—applicants who ranked among the Top20 companies are more likely to have secured outside financing prior to application in the accelerator. Further inspection reveals that such capital arises from two sources: grants and venture capital.

Figure A4, below, plots the distribution of normalized ranks across the cohorts. The solid line depicts the coefficients estimates and the dashed line the 95th confidence interval. The dots correspond to simple averages of the outcome variables for bins of size 1 of normalized score.

Figure A4: Characteristics of Applicants at the Application Stage



The final piece of evidence against the empirical relevance of ranking manipulation, is the insensitivity of results to controlling for differences in outside financing at the application stage. Table A6 shows that the size of the discontinuity are invariant to including a dummy of outside financing at the application stage as a control variable. The F-test continues to surpass the rule of thumb of 10. While it is impossible to fully test the assumption of no sorting on observables in the neighbourhood of the interview threshold (i.e., the staff at the accelerator observe more data than the econometrician), taken together the preponderance of evidence suggests the RD design is valid.

Table A6: Probability of Acceleration controlling for differences in outside financing at application. The table presents estimates of different specification of equation (1). The standard errors are presented in parentheses and are adjusted for heteroscedasticity and clustered at the normalized rank level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var. Acceleration	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Top20	0.182***	0.163***	0.176***	0.146***	0.187**	0.195***	0.147***
	(0.044)	(0.049)	(0.047)	(0.046)	(0.078)	(0.065)	(0.045)
Top 20×High				0.018	-0.009	-0.011	0.012
				(0.079)	(0.106)	(0.082)	(0.068)
Z	-0.000	-0.004	-0.000	-0.001	-0.007	-0.002	-0.001
	(0.002)	(0.005)	(0.002)	(0.002)	(0.009)	(0.002)	(0.002)
Z×High				0.001	0.005	0.002	
				(0.004)	(0.014)	(0.004)	
Z×Top 20	-0.034**	-0.038	-0.045	-0.022	0.071	0.059	-0.023
	(0.017)	(0.046)	(0.044)	(0.018)	(0.047)	(0.040)	(0.018)

Dep. Var. Acceleration	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Z×Top 20×High				-0.082***	-0.047	-0.036	-0.079***
				(0.021)	(0.089)	(0.081)	(0.021)
Z2		0.000			0.000		
		(0.000)			(0.000)		
Z2× High					-0.000		
					(0.000)		
Z2×Top 20		-0.001	-0.001		0.008*	0.007*	
		(0.004)	(0.004)		(0.004)	(0.004)	
Z2×Top 20×High					0.022	0.022	
					(0.015)	(0.015)	
Outside Financing	0.032*	0.030*	0.032*	0.030*	0.031*	0.031*	0.030**
	(0.017)	(0.017)	(0.017)	(0.015)	(0.016)	(0.016)	(0.015)
Observations	638	638	638	638	638	638	638
R2	0.226	0.228	0.227	0.261	0.276	0.275	0.261

Dep. Var. Acceleration	(1)	(2)	(3)	(4)	(5)	(6)	(7)
F All excluded instruments	18.77	11.99	15.32	40.88	24.56	94.01	60.88

5.5.2 Exploiting the Interview Threshold

We estimate a local average treatment effect of acceleration on venture performance by instrumenting acceleration, with the interview rule in a fuzzy RD design. We estimate a system of equations using (1) above and the following: In detail, we estimate the following system of equations:

$$(2)\ outcomes_i = \delta * acceleration_i + g(Z_i) + g^{'}(Z_i) * Top20 + \pi X_i + cohortFE + \varepsilon_i$$

where outcome measures company performance. g(Zi) and g'(Zi) are linear polynomials on the normalized rank Z, that include interactions with 2-quantiles of number of applicants that tie at the 20-th rank. Some specifications use controls Xi in order to reduce sampling variability and control for some visible differences in characteristics at application (see Figure A4). As with all instrumental variable estimators, inference based on our fuzzy RD is restricted to those observations that respond to the instrument; that is, applicants that are randomized into the accelerator by the interview rule.

Appendix 5.6. Supplementary results for analysis of one corporate accelerator on participating startups

Results are summarized in Tables A7 - A9. We present results using two different specifications of the system of equations (1)-(2). The corresponding first-stage results for columns 1-3 (4-6) in each panel are reported in column 4 (7) of Appendix 4, Table A6.

We find evidence of impacts on our three outcomes variables: online presence (Table A7), change in employees (Table A8), and change in fundraising (Table A9).

The interpretation of the coefficient in column 6 of Table A7 is that acceleration leads to an increase of 50% in online presence for the applicants at the margin of acceleration. Column 4 in the same table shows evidence of downward bias in the OLS estimate that compares average online presence between participants and rejected applicants, and does not control for endogeneity in participation. This downward bias likely reflects differences between average applicants, and those applicants at the margin of acceleration (i.e., those whose participation is affected by the selection rule), as is common in the estimation of local average treatment effects.

Table A7: Online Presence and Acceleration. The table presents results from estimating different specifications of the system of equations (1)-(2). The standard errors are presented in parentheses and are adjusted for heteroscedasticity and clustered at the normalized rank level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dep. Var. Online Presence	**OLS**	**RF**	**IV**	**OLS**	**RF**	**IV**
Acceleration	0.218***		0.377	0.226***		0.520**
	(0.037)		(0.250)	(0.037)		(0.235)
Top20		0.110			0.101	
		(0.090)			(0.089)	
Top 20×High		-0.102			-0.032	
		(0.143)			(0.118)	
Z	-0.003	-0.003	-0.003	-0.006**	-0.005*	-0.004
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Z×High	-0.009*	-0.011	-0.008			
	(0.005)	(0.007)	(0.006)			
Z×Top 20	0.022	0.024	0.028*	0.031**	0.031*	0.040**
	(0.014)	(0.016)	(0.015)	(0.015)	(0.018)	(0.017)
Z×Top 20×High	0.044	0.017	0.058	0.010	-0.008	0.042
	(0.032)	(0.029)	(0.040)	(0.021)	(0.026)	(0.034)
Observations	638	638	638	638	638	638

	(1)	(2)	(3)	(4)	(5)	(6)
R2	0.226	0.228	0.227	0.261	0.276	0.275

The interpretation of the coefficient in column 6 of Table A8 is that acceleration increases employment growth, helping applicants transition up, by roughly one level, in the online classification of employee size. Given that the average applicant has 5 employees at application (i.e., the first level of online employee size: 1-10 employees), the estimated average transition is towards the second level of employee size: between 11 and 50 employees. Similarly to the effect on online presence, a comparison between column 4 and column 6 reveals that an OLS comparison between accelerated and rejected applicants underestimates the effect of acceleration on employee growth for companies at the margin of acceleration (i.e., those whose participation is affected by the selection rule of the accelerator).

Finally, the interpretation of the coefficient in column 6 of Table A9 is that acceleration increases fundraising by 77.6%. A comparison between columns 4 and 7 shows that similar to the OLS biases for online presence and employee growth, not controlling for selection effects in estimating the effect of acceleration biases downwards the estimated effect. We present results controlling for differences at application in the probability of having secured outside financing by the application; corresponding first-stage results for columns 1-3 (4-6) are presented in column 4(7) of Table A6. Results are quantitatively similar if we do not control for this difference at the application stage. Results are also robust to using changes in the level of fundraising, rather than changes in logarithms. We present results using the changes in logarithms, to control for the effect of outliers in the data.

Table A8: Employee Growth and Acceleration. The table presents results from estimating different specifications of the system of equations (1)-(2). The standard errors are presented in parentheses and are adjusted for heteroscedasticity and clustered at the normalized rank level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dep. Var. Changes in Employees	**OLS**	**RF**	**IV**	**OLS**	**RF**	**IV**
Acceleration	0.676***		0.870	0.689***		1.127**
	(0.158)		(0.570)	(0.157)		(0.538)
Top20		0.336**			0.314**	
		(0.162)			(0.155)	
Top 20×High		-0.400			-0.240	
		(0.288)			(0.219)	
Z	-0.006	-0.004	-0.005	-0.010	-0.009	-0.008
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Z×High	-0.015	-0.026	-0.014			
	(0.018)	(0.021)	(0.020)			
Z×Top 20	0.068	0.075	0.075	0.083	0.090*	0.096
	(0.052)	(0.052)	(0.058)	(0.051)	(0.053)	(0.059)
Z×Top 20×High	0.088	-0.005	0.104	0.031	-0.062	0.078
	(0.113)	(0.096)	(0.120)	(0.086)	(0.086)	(0.102)

Observations	638	638	638	638	638	638
R2	0.226	0.228	0.227	0.261	0.276	0.275

Table A9: Fundraising Growth and Acceleration. The table presents results from estimating different specifications of the system of equations (1)-(2). The standard errors are presented in parentheses and are adjusted for heteroscedasticity and clustered at the normalized rank level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dep. Var. Changes in Fundraising	**OLS**	**RF**	**IV**	**OLS**	**RF**	**IV**
Acceleration	0.617***		1.063***	0.607***		0.776***
	(0.136)		(0.271)	(0.135)		(0.257)
Top20		-0.026			0.006	
		(0.052)			(0.059)	
Top 20×High		0.278***			0.042	
		(0.094)			(0.100)	
Z	-0.000	-0.002	0.000	0.007	0.005	0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Z×High	0.029***	0.038***	0.029***			
	(0.008)	(0.010)	(0.008)			
Z×Top 20	0.020	-0.000	0.026	-0.006	-0.022	-0.015
	(0.028)	(0.030)	(0.027)	(0.029)	(0.030)	(0.028)
Z×Top 20×High		-0.026			0.006	

		(0.052)			(0.059)	
Outside Financing	-0.485***	-0.470***	-0.502***	-0.496***	-0.482***	-0.503***
	(0.059)	(0.058)	(0.064)	(0.058)	(0.058)	(0.062)
Observations	638	638	638	638	638	638
R2	0.120	0.102	0.118	0.111	0.090	0.102

Appendix 5.7 Supplementary methodology for estimating the effect of the type of support provided by accelerators and incubators on startup outcomes

Estimation techniques follow the type of dependent variable that is being modelled in any particular case. Most models are ordinary least squares (OLS) regressions, while for binary choice variables or count data, such as patents, we use Probit, Poisson or Negative Binomial models. All models of startup support control for industry sector, development stage, size and the year in which the startup joined the programme.

Table A10: Definitions of dependent variables in estimations of startup support. This table shows variable definitions for our main regressions that test the impact on startups of support and mentoring received from accelerator and incubators.

Variable	Definition
Perceived impact	Perceived impact is measured as startup's answer to the question "Looking back, what impact has the support provided by [programme name] had on this enterprise's chance of success?" assigning a numerical value: -1 = Negative, 0 = None, 1 = Minor, 2 = Significant, 3 = Vital.
Employment growth	Growth in employment is defined as Log(employment in the last financial year + 1) - Log(employment when joining the programme + 1), divided by the number of years since joining the accelerator. If the last financial year for which data is available is the same as the year in which the respondent joined the programme, we assume that the period over which growth is measured is half a year.
Growth in employees with a degree	The number of employees with a degree is derived from the question, "If any of the employees above hold a degree or postgraduate qualification, please provide a rough estimation of how many. "Growth in the proportion of employees with a degree is defined as (number of employees with a degree in the last financial year − number of employees with a degree when joining

	the programme)/(number of employees with a degree when joining the programme + 1).
Development stage	A startup's development stage is defined at the time when applying to a programme and when completing the survey. Possible stages when applying to a programme are Idea-stage (did not yet have a working prototype or customers), Prototype-stage (had a working prototype but had not yet earned revenue), Post-revenue stage (had customers and functioning revenue models but was not yet cash-flow positive), Growth-stage (was operating at scale and was typically cash flow positive), Mature-stage, and similarly for the startup's current stage.
Innovation	Innovation is measured as a respondent's answer to the question, "Since applying to [name of accelerator/incubator], has this enterprise introduced a new or significantly improved product, process or service to market?"; dummy variable.
Patents	The number of patents is measured as the response to the question, "If your enterprise has submitted any patent applications since applying to [name of accelerator/incubator], please enter how many. (Enter 0 if no applications were submitted)"
R&D expenditure	R&D expenditure is derived from the question, "What was this enterprise's total approximate research and development (R&D refers to any activity undertaken in developing new or improving existing products or services) expenditure in the last financial year?"; in pounds sterling.
Investment raised	The investment raised, used as a dependent variable, is a dummy variable that is equal to one if the total investment received by the respondent in the most fiscal year is greater than the investment received until joining the programme. It is based on the question, "Approximately how much investment (equity, convertible notes, grants, but not loans) has this enterprise received from outside sources? … Before applying to [programme] … Total investment received to date (since inception of the enterprise, excluding any received from [programme name])".

Table A11: Definitions of independent variables of interest

Variable	Definition
Support by accelerator	
Access to partners & customers	
Access to investors	Support variables are answers to the question, "During this enterprise's time in [programme name], did it receive any of the following, and was it useful to the enterprise?"
Access to peers	
Testing & refining business model	These dummy variables are equal to one if the type of support was received and zero otherwise.

Help with team formation	
Direct funding from the programme	
Business skills development	
Press or media exposure	
Lab space or equipment	
Legal, financial, marketing or HR support	
Help measuring social impact	
Office space	
Coaching / personal development	
Mentoring	
Industry expert	Mentoring types are answers to the question, “Did any of this enterprise's mentors during [name of accelerator/incubator] fall into the following categories?” These dummy variables are equal to one if the type of mentoring was received and zero otherwise.
Entrepreneur (exited a venture)	
Entrepreneur (not exited)	
VC / angel	
Consultant, business developer	
Mentoring intensity	Mentoring intensity is the response to the question, “During this enterprise's time in {{programme name}}, roughly how many hours per week did directors and employees of your enterprise spend in one-to-one mentoring?”, coded numerically into 0 = “None” to 8 = “17+ hours/ week” according to Table XX5.

Table A12: Definitions of control variables

Variable	Definition
Accelerators joined in the past	Number of other accelerators or incubators in which the startup has participated or is currently participating
Stage before	The enterprise's development stage when applying to the programme; can be one of {idea, prototype, post-revenue, growth}; dummy variable
Employees when joining	Number of people working for the enterprise, including full-time equivalent part-time employees (but excluding contract workers who are not on the business' official payroll)
Currently participating in programme	The enterprise is currently participating in an accelerator or incubator programme; dummy variable.
Year	The year in which the enterprise joined an accelerator or incubator
Industry sector	One of eight broad sectors, using Beauhurst's sector classification and aggregated based on UK-SIC 2007 codes to achieve meaningful cell counts: 1: Agritech, extractive industries, construction, transport, retail 2: Professional services (life sciences, marketing technology, space and satellite technology, finance (incl. fintech and insurance tech) 3: Public sector (civtech, smart cities) 4: Manufacturing (cleantech, engineering, food) 5: Arts (creative industries and design, leisure) 6: Information technology (cyber security, digital (including generalist AI & generalist blockchain), Internet of Things (IoT), telecommunication) 7: Education 8: Health and wellbeing

Appendix 5.8. Mentoring received by survey participants

Table A13: Mentoring support. This table shows how many hours per week directors and employees of startups spent in one-to-one mentoring while participating in an accelerator or incubator.

	Full sample		Accelerators		Other programmes[57]	
Duration	**N**	**%**	**N**	**%**	**N**	**%**
None	31	11%	19	9%	12	19%
Less than 1 hour/ week	98	36%	72	34%	26	42%
1-2 hours / week	77	28%	62	30%	15	24%
3-4 hours / week	34	13%	28	13%	6	10%
5-8 hours / week	15	6%	14	7%	1	2%
9-16 hours / week	11	4%	10	5%	1	2%
17+ hours/ week	6	2%	5	2%	1	2%
	272	100%	210	100%	62	100%

Table A14: Mentor types. This table shows whether any of the startups' mentors during their participation in an accelerator or incubator fall into any of the mentoring categories.

Mentor type	N =	Yes	No	Don't know
Industry expert	267	58%	34%	9%
Entrepreneur who had previously sold a business	267	57%	33%	11%
Entrepreneur who had not sold a business	259	51%	33%	17%
Venture capitalist or business angel	262	45%	43%	12%
Consultant, business developer	263	67%	22%	11%

[57] "Other" programmes includes 44 startups in incubators, 1 in a coworking space, 1 in a coworking space plus, 9 in "other" programmes (in The Startup Tribe, UnLtd, Activate Capital, Entrepreneur First) and 7 missing values on programme type.

Appendix 5.9. Improvements suggested by startups

Table A15: Improvements suggested by startups. This table shows potential improvements that are mentioned by startups in their free comments to the startup survey, which we have clustered by theme. Numbers in parentheses show the number of occurrences for each improvement. Improvements with fewer than two mentions per theme have been omitted.

Theme	Improvement mentioned by startups
Funding	Further funding: help in getting more funding, access to investors, preparation in getting public funding, high-impact fundraising strategy, angel pitching events (x10)
	Direct funding during the programme (e.g., in the form of equity), or additional funding based on quality of business proposition (x3)
	Lower cost of capital for social businesses
	Financial management help
	But: too much focus on pitching to investors
Mentoring	More mentors with specific industry experience, thought leaders in the industry; but mentors need to be engaged (x8)
	More general mentoring: support from entrepreneurs as mentors, one-to-one, online talks (x6)
	Greater availability of support by the programme director, needs to be 100% dedicated to the programme (x2)
	Less turnover of mentors
Long-term support	Long-term perspective needed, particularly for social businesses; pressure to get VC is not always optimal (x8)
Peers and community	Help with the social aspect (working in a small team can feel lonely) (x2)
	Investigate possibilities of peer support (x2)
	Have people with similar businesses work together
Market	More introductions to customers, qualified leads; focus on market fit (x5)
Exit from the programme	Support after the accelerator to bridge the “valley of death”; updates and advice, not just events (x4)
	Support when leaving the programme to manage the transition

Appendix 5.10. Impact of support activities

Table A16: Impact of support on perceived impact of programmes. The dependent variable is the startups' perception of the impact that accelerators and incubators had on their success. All models include effects for industry sectors and the year of joining the programme. Model 2 is optimised to keep only variables with p<0.1, starting with model 1 and removing the least significant variable until only significant variables remain. Standard errors clustered by programme are in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	(1)			**(2)**		
	Full model			**Optimised**		
Model:	**OLS**			**OLS**		
Support by programme						
Access to partners & customers	0.339	(0.15)	**	0.379	(0.11)	***
Access to investors	-0.097	(0.13)				
Access to peers	0.369	(0.26)				
Testing & refining business model	0.383	(0.15)	**	0.402	(0.12)	***
Help with team formation	0.439	(0.13)	***	0.467	(0.10)	***
Direct funding from the programme	0.284	(0.15)	*	0.280	(0.11)	**
Business skills development	0.240	(0.21)				
Press or media exposure	0.120	(0.15)				
Lab space or equipment	-0.103	(0.20)				
Legal, financial, marketing or HR support	0.329	(0.20)		0.345	(0.20)	*
Help measuring social impact	0.153	(0.11)				
Office space	-0.031	(0.15)				
Coaching / personal development	-0.067	(0.17)				
Mentoring						
Industry expert	0.229	(0.13)	*	0.207	(0.12)	*
Entrepreneur (exited a venture)	0.055	(0.16)				
Entrepreneur (not exited)	-0.004	(0.11)				

VC / angel	0.055	(0.15)				
Consultant, business developer	-0.060	(0.16)				
Mentoring intensity	-0.007	(0.05)				
Control variables						
Accelerators joined in the past	-0.020	(0.07)				
Stage before: Idea	0.418	(0.22)	*	0.563	(0.19)	***
Stage before: Post-revenue	0.029	(0.24)		0.174	(0.18)	
Stage before: Prototype	0.209	(0.23)		0.351	(0.18)	*
Employees when joining	-0.011	(0.10)				
Currently participating in programme	0.321	(0.14)	**	0.302	(0.12)	**
Observations	230			254		
F-stat. p-value	0.000			0.000		
R-squared	0.445			0.389		
R-squared (adj.)	0.328			0.364		

Table A17: Impact of support on employment growth. The dependent variable is the growth in employment, defined as Log(employment when joining the programme + 1) - Log(employment today), divided by the number of years since joining the programme. All models include effects for industry sectors and the year of joining the programme. Model 2 is optimised to keep only variables with p<0.1, starting with model 1 and removing the least significant variable until only significant variables remain. Standard errors clustered by programme are in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	(1)			**(2)**		
	Full model			**Optimised**		
Model:	**OLS**			**OLS**		
Support by programme						
Access to partners & customers	-0.039	(0.07)				
Access to investors	-0.006	(0.07)				
Access to peers	0.341	(0.11)	***	0.265	(0.10)	**
Testing & refining business model	-0.320	(0.12)	**	-0.314	(0.10)	***

Help with team formation	0.128	(0.07)	*	0.117	(0.06)	**
Direct funding from the programme	0.144	(0.08)	*	0.153	(0.06)	**
Business skills development	-0.159	(0.11)				
Press or media exposure	0.212	(0.07)	***	0.134	(0.06)	**
Lab space or equipment	-0.115	(0.08)				
Legal, financial, marketing or HR support	-0.157	(0.08)	**			
Help measuring social impact	0.160	(0.11)				
Office space	0.050	(0.08)				
Coaching / personal development	0.034	(0.09)				
Mentoring						
Industry expert	-0.055	(0.08)				
Entrepreneur (exited a venture)	0.017	(0.08)				
Entrepreneur (not exited)	-0.063	(0.07)				
VC / angel	0.237	(0.10)	**	0.136	(0.07)	**
Consultant, business developer	-0.271	(0.07)	***	-0.256	(0.07)	***
Mentoring intensity	0.085	(0.05)	*	0.060	(0.03)	*
Control variables						
Accelerators joined in the past	-0.057	(0.06)				
Stage before: Idea	-0.116	(0.11)				
Stage before: Post-revenue	-0.072	(0.12)				
Stage before: Prototype	-0.057	(0.14)				
Employees when joining	-0.233	(0.05)	***	-0.191	(0.04)	***
Currently participating in programme	-0.128	(0.08)	*	-0.126	(0.05)	**
Observations	229			240		
F-stat. p-value	0.000			0.000		
R-squared	0.426			0.353		
R-squared (adj.)	0.304			0.309		

Table A18: Impact of support on employees with a degree. The dependent variable is the growth in the proportion of employees with a degree, scaled by the number of years since joining the programme. All models include effects for industry sectors and the year of joining the programme. Model 2 is optimised to keep only variables with p<0.1, starting with model 1 and removing the least significant variable until only significant variables remain. Standard errors clustered by programme are in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	(1)			**(2)**		
	Full model			**Optimised**		
Model:	**OLS**			**OLS**		
Support by programme						
Access to partners & customers	0.372	(0.47)				
Access to investors	-0.029	(0.28)				
Access to peers	1.041	(0.43)	**	1.226	(0.50)	**
Testing & refining business model	-1.285	(0.59)	**	-1.150	(0.63)	*
Help with team formation	0.065	(0.36)				
Direct funding from the programme	0.292	(0.27)				
Business skills development	-1.491	(0.93)				
Press or media exposure	0.246	(0.20)				
Lab space or equipment	0.049	(0.58)				
Legal, financial, marketing or HR support	-0.551	(0.32)	*			
Help measuring social impact	0.988	(0.53)	*	0.875	(0.41)	**
Office space	-0.236	(0.30)				
Coaching / personal development	0.519	(0.52)				
Mentoring						
Industry expert	-0.153	(0.39)				
Entrepreneur (exited a venture)	-0.299	(0.42)				
Entrepreneur (not exited)	0.013	(0.32)				
VC / angel	0.895	(0.43)	**	0.718	(0.27)	***
Consultant, business developer	-1.109	(0.41)	***	-1.115	(0.46)	**

Mentoring intensity	0.312	(0.23)				
Control variables						
Accelerators joined in the past	-0.192	(0.17)				
Stage before: Idea	-1.238	(1.14)				
Stage before: Post-revenue	-0.892	(0.78)				
Stage before: Prototype	-1.418	(1.10)				
Employees when joining	-0.919	(0.37)	**	-0.609	(0.20)	***
Currently participating in programme	-0.485	(0.38)		-0.526	(0.29)	*
Observations	224			238		
F-stat. p-value	0.000			0.000		
R-squared	0.341			0.177		
R-squared (adj.)	0.197			0.141		

Table A19: Impact of support on development stage. The binary dependent variable indicates whether the startup has progressed to a further development stage after joining an accelerator or incubator programme. The assumed stage sequence is {dead, idea stage, prototype stage, post-revenue stage, growth stage, mature stage}. The sample excludes 1 acquired startup, 4 startups with "other" or missing stage, as well as all 17 startups at the growth stage, which did not change their development stage. All models include effects for industry sectors and the year of joining the programme. Model 2 is optimised to keep only variables with $p<0.1$, starting with model 1 and removing the least significant variable until only significant variables remain. Standard errors clustered by programme are in parentheses. Significance levels: *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

	(1)			**(2)**		
	Full model			**Optimised**		
Model:	**Probit**			**Probit**		
Support by programme						
Access to partners & customers	0.733	(0.56)				
Access to investors	-0.233	(0.50)				
Access to peers	0.401	(0.46)				
Testing & refining business model	0.249	(0.35)				

Help with team formation	1.147	(0.38)	***	0.724	(0.26)	***
Direct funding from the programme	0.466	(0.36)				
Business skills development	0.271	(0.46)				
Press or media exposure	-0.448	(0.38)				
Lab space or equipment	-0.684	(0.48)				
Legal, financial, marketing or HR support	-0.467	(0.31)				
Help measuring social impact	-0.298	(0.28)				
Office space	0.270	(0.32)				
Coaching / personal development	-1.569	(0.66)	**	-0.663	(0.33)	**
Mentoring						
Industry expert	0.556	(0.50)				
Entrepreneur (exited a venture)	-0.211	(0.56)				
Entrepreneur (not exited)	-0.732	(0.45)				
VC / angel	-0.085	(0.40)				
Consultant, business developer	0.292	(0.34)				
Mentoring intensity	-0.008	(0.17)				
Control variables						
Accelerators joined in the past	-0.119	(0.19)				
Stage before: Idea						
Stage before: Post-revenue	-2.133	(0.51)	***	-1.438	(0.27)	***
Stage before: Prototype	-0.984	(0.40)	**	-0.659	(0.24)	***
Employees when joining	-0.304	(0.25)				

Currently participating in programme	-0.883	(0.40)	**	-0.613	(0.24)	**
Observations	215			245		
McFadden R-squared	0.450			0.303		
McFadden R-squared (adj.)	0.149			0.255		
AIC	217.034			217.585		
Chi-sq. p-value	0.000			0.000		
Log-Likelihood	-69.517			-100.793		

Table A20: Impact of support on innovation. The binary dependent variable indicates whether the startup has introduced a new or significantly improved product, process or service to market since applying to an accelerator or incubator programme. All models include effects for industry sectors and the year of joining the programme. Model 2 is optimised to keep only variables with p<0.1, starting with model 1 and removing the least significant variable until only significant variables remain. Standard errors clustered by programme are in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	(1)			**(2)**		
	Full model			**Optimised**		
Model:	**Probit**			**Probit**		
Support by programme						
Access to partners & customers	0.071	(0.30)				
Access to investors	-0.171	(0.31)				
Access to peers	0.546	(0.55)				
Testing & refining business model	-0.539	(0.27)	**			
Help with team formation	0.389	(0.27)		0.335	(0.18)	*
Direct funding from the programme	0.964	(0.33)	***	0.798	(0.22)	***
Business skills development	-0.260	(0.46)				

Press or media exposure	-0.191	(0.24)				
Lab space or equipment	0.025	(0.28)				
Legal, financial, marketing or HR support	0.096	(0.25)				
Help measuring social impact	0.524	(0.20)	***			
Office space	-0.072	(0.36)				
Coaching / personal development	0.060	(0.29)				
Mentoring						
Industry expert	0.701	(0.28)	**	0.545	(0.28)	**
Entrepreneur (exited a venture)	0.239	(0.35)				
Entrepreneur (not exited)	-0.260	(0.30)				
VC / angel	0.025	(0.24)				
Consultant, business developer	-0.442	(0.24)	*	-0.320	(0.19)	*
Mentoring intensity	-0.063	(0.12)				
Control variables						
Accelerators joined in the past	-0.050	(0.13)				
Stage before: Idea	0.125	(0.70)				
Stage before: Post-revenue	-0.567	(0.65)		-0.402	(0.18)	**
Stage before: Prototype	-0.529	(0.48)				
Employees when joining	-0.040	(0.18)				
Currently participating in programme	-0.698	(0.29)	**	-0.513	(0.26)	*

Observations	234	258
McFadden R-squared	0.248	0.171
McFadden R-squared (adj.)	-0.057	0.102
AIC	279.112	261.576
Chi-sq. p-value	0.008	0.000
Log-Likelihood	-98.556	-119.788

Table A21: Impact of support on patenting. The dependent variables in these models measure the patenting activity of startups. Model 1 is a log-linear model of the number of patents applications submitted since applying to the accelerator or incubator programme, model 2 uses the same variable but collapses it into a binary indicator of whether a startup is patenting, and model 3 uses a negative binomial model to predict the number of patents. All models have been optimised to keep only variables with p<0.1, starting with model 1 and removing the least significant variable until only significant variables remain. Standard errors in parentheses are clustered by programme for models 1 and 2, and ordinary standard errors for model 3. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	(1)			**(2)**			**(3)**		
Dependent variable:	**Patents (log)**			**Patents>0**			**Patents**		
Model:	**OLS**			**Probit**			**Neg. Binomial**		
Support by programme									
Access to partners & customers	-0.148	(0.08)	*						
Access to investors							0.942	(0.39)	**
Testing & refining business model							-1.472	(0.53)	***
Business skills development	-0.239	(0.13)	*				-1.734	(0.43)	***
Press or media exposure	0.176	(0.06)	***	0.687	(0.26)	***			
Legal, fin., marketing or HR support				-0.683	(0.32)	**			

Office space							-0.914	(0.37)	**
Coaching / personal development	0.184	(0.11)	*				1.349	(0.42)	***
Mentoring									
Consultant, business developer	0.178	(0.06)	***	0.555	(0.32)	*	1.004	(0.42)	***
Mentoring intensity				0.254	(0.12)	**	0.479	(0.15)	***
Control variables									
Accelerators joined in the past	0.146	(0.05)	***	0.339	(0.13)	**	0.597	(0.15)	***
Stage before: Idea	0.406	(0.11)	***						
Stage before: Post revenue	0.108	(0.06)	*	-1.147	(0.32)	***	-2.229	(0.62)	***
Stage before: Prototype	0.211	(0.07)	***				-0.853	(0.36)	**
Currently participating in programme	-0.201	(0.09)	**	-0.893	(0.33)	***	-1.850	(0.58)	***
Observations	237			218			216		
F-stat. p-value	0.000								
R-squared	0.252								
R-squared (adj.)	0.208								
McFadden R-squared				0.257			0.176		
McFadden R-squared (adj.)				0.173			0.121		
AIC				180.941			322.544		
Chi-sq. p-value				0.000			0.000		
Log-Likelihood				-80.470			-53.690		

Table A22: Impact of support on R&D. The dependent variables in these models measure the expenditures for research and development (R&D) of startups in the most recent financial year. Model 1 is a log-linear model of (R&D expenditures + 1), model 2 is the optimised version of this model which keeps only variables with p<0.1, starting with model 1 and removing the least significant variable until only significant variables remain. The dependent variable in Model 3 in an indicator variables that is equal to one if the startup reports positive R&D expenditures in the most recent financial year. All models include year and sector effects (optimised models only if significant). Standard errors in parentheses are clustered by programme. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	(1)			**(2)**			**(3)**		
Dependent variable	**Full model**			**Optimised**			**Optimised**		
Model	**OLS**			**OLS**			**Probit**		
Support by programme									
Access to partners & customers	-0.296	(0.87)							
Access to investors	1.121	(1.18)		1.820	(0.67)	***			
Access to peers	0.969	(1.36)							
Testing & refining business model	-1.613	(0.92)	*						
Help with team formation	0.535	(0.59)							
Direct funding from the programme	1.914	(0.67)	***	2.022	(0.63)	***	0.714	(0.24)	***
Business skills development	0.071	(1.21)							
Press or media exposure	0.279	(0.70)							
Lab space or equipment	-1.512	(0.82)	*				-0.560	(0.24)	**
Legal, financial, marketing or HR support	-0.952	(0.72)		-0.982	(0.57)	*	-0.391	(0.18)	**
Help measuring social impact	0.639	(0.66)							
Office space	0.781	(0.84)					0.778	(0.30)	***
Coaching / personal development	-0.442	(0.82)							

Mentoring									
Industry expert	-0.237	(0.64)							
Entrepreneur (exited a venture)	0.092	(0.94)							
Entrepreneur (not exited)	0.432	(0.66)							
VC / angel	0.897	(1.13)					0.440	(0.20)	**
Consultant, business developer	-0.499	(0.65)							
Mentoring intensity	0.039	(0.31)							
Control variables									
Accelerators joined in the past	0.562	(0.28)	**	0.387	(0.22)	*	0.389	(0.19)	**
Stage before: Idea	3.651	(1.37)	***	2.412	(1.26)	*			
Stage before: Post revenue	1.440	(1.03)							
Stage before: Prototype	2.850	(1.13)	**	1.614	(0.81)	**			
Employees when joining	1.978	(0.50)	***	1.774	(0.56)	***	0.473	(0.14)	***
Currently participating in programme	-1.497	(0.72)	**				-0.512	(0.24)	**
Observations	225			254			245		
F-stat. p-value	0.000			0.000					
R-squared	0.399			0.309					
R-squared (adj.)	0.268			0.281					
McFadden R-squared							0.300		
McFadden R-squared (adj.)							0.199		
AIC							223.915		
Chi-sq. p-value							0.000		

Log-Likelihood				-96.958		

Table A23: Impact of support on investment raised. The binary dependent variable in this table measures whether the total amount of outside investment (equity, convertible notes, grants, but not loans) raised by the startup is greater than the total amount raised before applying to the accelerator or incubator programme. Standard errors clustered by programme are in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

Model	(1) Full model Probit			(2) Optimised Probit		
Support by programme						
Access to partners & customers	-0.368	(0.26)				
Access to investors	0.770	(0.37)	**	0.793	(0.25)	***
Access to peers	-0.135	(0.71)				
Testing & refining business model	-0.966	(0.33)	***	-0.538	(0.22)	**
Help with team formation	0.191	(0.23)				
Direct funding from the programme	0.448	(0.24)	*	0.528	(0.20)	***
Business skills development	0.296	(0.38)				
Press or media exposure	0.149	(0.29)				
Lab space or equipment	-0.339	(0.32)				
Legal, financial, marketing or HR support	-0.795	(0.32)	**	-0.446	(0.22)	**
Help measuring social impact	0.412	(0.39)		0.512	(0.23)	**
Office space	0.378	(0.30)				
Coaching / personal development	0.142	(0.39)				
Mentoring						
Industry expert	-0.213	(0.27)				
Entrepreneur (exited a venture)	-0.065	(0.35)				

Entrepreneur (not exited)	-0.302	(0.22)				
VC / angel	0.304	(0.35)				
Consultant, business developer	-0.105	(0.36)				
Mentoring intensity	0.317	(0.22)				
Control variables						
Accelerators joined in the past	0.129	(0.18)				
Stage before: Idea	1.039	(0.32)	***	0.689	(0.23)	***
Stage before: Post-revenue	0.175	(0.34)				
Stage before: Prototype	0.507	(0.28)	*			
Employees when joining	0.201	(0.16)				
Currently participating in programme	-0.322	(0.30)				
Observations	215			239		
F-stat. p-value						
R-squared						
R-squared (adj.)						
McFadden R-squared	0.272			0.178		
McFadden R-squared (adj.)	-0.011			0.127		
AIC	287.918			277.414		
Chi-sq. p-value	0.000			0.000		
Log-Likelihood	-102.959			-129.707		

Table A24: Robustness test - impact of accelerator support. The table below shows the effects of support measures for the subsample of startups that participated in accelerators. Only the direction and significance of coefficients in optimised models analogous to those in tables A16-A23 are shown. For example, “+++” represents a coefficient that is positive and significant at the p<0.01 level. Similarly, “++” is a positive coefficient at the p<0.05 level, and “−“ is a negative coefficient at the p<0.1 significance level. Starred (*) coefficients are new compared to the main models using the full-sample of startups supported by accelerators and incubators; coefficients in parentheses become insignificant compared to full-sample models. Dependent variables are: impact of the programme as perceived by startups; employment growth; growth in the number of employees with a degree; progression to a higher stage in a firm life cycle; innovation of products, services or processes; whether a startup is patenting (probit model); R&D expenditures (Log); and whether any additional investment was raised since applying to the accelerator.

	Perceived impact	**Employment growth**	**Employees with a degree**	**Development stage**	**Innovation**	**Patenting**	**R&D (Log)**	**Investment raised**
Observations	180	172	173	176	188	160	196	184
Support by programme								
Access to partners & customers	+++			++*		−−−*		
Access to investors	++*						(++)	+++
Access to peers		+++	++					
Testing & refining business model	+++	−−−	(−)					−
Help with team formation	+++	++		+++	(+)			
Direct funding from the programme	(++)	+++			+++		+++	(+++)
Business skills development	++*			+*		−−−*		

Press or media exposure		+++		−−*		+++		
Lab space or equipment				−−*			−−*	
Legal, financial, marketing or HR support	(+)			−−*	+++*	(−−)	(−)	−−
Help measuring social impact			(++)		+*			+
Office space					−−−*			
Coaching / personal development				−−−		+*		
Mentoring support								
Industry expert	++				(++)			
Entrepreneur (not exited)	+++*			−−*				
VC / angel		++	+++					
Consultant, business developer		−−*	−−		(−)	++		
Mentoring intensity		(+)		++*		+++		++

Table A25: Development stage of startups. This table shows the observed relative transition frequencies of startups from their stage of development when applying to an accelerator or incubator to their development stage today.

Development stage at application	Development stage today								
	Idea	**Prototype**	**Post-revenue**	**Growth**	**Mature**	**Acquired**	**Dead**	**Other**	**N/A**
Idea	2.7 %	11.3%	9.5%	5.2%	0.0%	0.0%	0.5%	0.0%	0.0%
Prototype	0.2 %	8.6%	19.3 %	6.8%	0.0%	0.0%	0.9%	0.0%	0.0%
Post revenue	0.0 %	0.5%	14.5 %	10.0%	0.0%	0.2%	0.7%	0.2%	0.2%
Growth	0.0 %	0.0%	0.0%	7.7%	0.0%	0.0%	0.0%	0.0%	0.0%
Mature	0.0 %	0.0%	0.0%	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%
N/A	0.0 %	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%

Appendix 5.11. Latent class analysis

Table A26: Combinations of startup support. Table shows the results of a latent class analysis of startup support. Using six latent classes optimises the Akaike information criterion for the model with N=236 observations for which we have complete information on startup support and mentoring type. For each class of startup support, the model predicts how likely a respondent is to answer positively to each of the support and mentoring questions. For example, a value of 0.97 in the column of class 1 represents a likelihood of 97% that the respondent will have received office space if they are in class 1. The estimated proportion of startups in each class is shown in the first row.

	Latent class of support					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Estimated class population shares	0.19	0.42	0.07	0.10	0.05	0.17
Support type						
Direct funding from the programme	0.90	0.44	0.00	0.24	0.23	0.27
Office space	0.97	0.74	1.00	0.53	0.28	0.72
Lab space or equipment	0.33	0.19	0.17	0.19	0.00	0.15
Access to peers	1.00	1.00	1.00	0.74	0.53	1.00
Coaching / personal development	1.00	0.91	1.00	0.54	0.38	0.82
Testing & refining business model	0.94	0.88	1.00	0.23	0.58	0.62
Business skills development	0.98	1.00	1.00	0.35	0.45	0.76
Access to partners & customers	1.00	0.89	0.73	0.59	0.37	0.31
Help measuring social impact	0.52	0.20	0.27	0.05	0.15	0.16
Legal, financial, marketing or HR support	0.91	0.84	0.97	0.22	0.09	0.57
Press or media exposure	0.79	0.71	0.74	0.87	0.00	0.19
Help with team formation	0.81	0.49	0.80	0.00	0.00	0.13
Access to investors	1.00	0.92	0.66	0.71	0.26	0.35
Mentoring type						
Industry expert	0.83	0.64	0.00	0.49	0.57	0.32
Entrepreneur (exited a venture)	0.95	0.71	0.00	0.10	1.00	0.08
Entrepreneur (not exited)	0.95	0.57	0.00	0.00	0.52	0.26

VC / angel	0.87	0.57	0.00	0.09	0.47	0.00
Consultant, business developer	1.00	0.71	0.17	0.32	0.48	0.58

Table A27: Impact of programme types. The table below shows the effects if startups receive any of the six combinations of support defined in Table A26. For these six combinations (i.e., programme types or latent classes of support), the table shows direction and significance of coefficients in our main models in Appendix 5.10, if support and mentoring variables are replaced with the estimated likelihood of a startup receiving support from any of the programme types (i.e. membership in the latent support classes) defined in Table A26, relative to the effect of belonging to latent class 1 (high-intensity support). For example, "+++" represents a coefficient that is positive and significant at the p<0.01 level. Similarly, "++" is a positive coefficient at the p<0.05 level, and "−" is a negative coefficient at the p<0.1 significance level. Dependent variables are: Perceived impact of accelerators perceived by startups; employment growth; growth in the number of employees with a degree; progression to a higher stage in a firm life cycle; innovation of products, services or processes; number of patents (Log); R&D expenditures (Log); and whether any additional investment was raised since applying to the accelerator.

	Perceived impact	**Employment growth**	**Employees with a degree**	**Development stage**	**Innovation**	**Patents (Log)**	**R&D (Log)**	**Investment raised**
2: Accelerator-like							−−	
3: Mentoring-free	−						−−−	−
4: External exposure	−−−		−		−			−
5: Mentoring focus	−−−	−					−−−	
6: Incubator-like	−−−	−		−	−		−−−	

Appendix 5.12 Impact on and effects of intermediate outcomes

Table A28: Support and intermediate outcomes. The table below shows the direction and significance of coefficients in optimised models for intermediate outcomes, regressed on support types. For example, "+++" represents a coefficient that is positive and significant at the p<0.01 level. Similarly, "++" is a positive coefficient at the p<0.05 level, and "−" is a negative coefficient at the p<0.1 significance level. Intermediate outcomes are: Strategic planning, Product development, Recruiting and developing staff, Marketing, Attracting and keeping customers, Where to locate the enterprise, Raising Finance, Partnerships with external organisations, Leading and management, Managing cash flow, Adopting new digital technologies (e.g. Customer Relationship Management (CRM), Marketing Automation or Project Management software). To maximise the amount of non-missing data, we test one support variable at a time in addition to the predictors that were found significant in our optimised models for outcome measures.

	Intermediate outcome				
	Strategic Planning	**Product Dev.**	**Recruiting**	**Marketing**	**Location**
Support by programme					
Access to partners & customers	+++				
Access to investors				+	−−
Access to peers					
Testing & refining business model		++			
Help with team formation	++	++	+++	+++	+++
Direct funding from the programme					
Business skills development		−−−		−	
Press or media exposure				+++	
Lab space or equipment					++
Legal, financial, marketing or HR support		+			+
Help measuring social impact	+	+++			
Office space			++		++

Coaching / personal development	+++			+++	
Mentoring support					
Industry expert		+			
Entrepreneur (exited a venture)	+++		+		
Entrepreneur (not exited)					
VC / angel				++	
Consultant, business developer	−	+			++
Mentoring intensity		+++			

continued on next page

Table A28 (continued): Support and intermediate outcomes

	Intermediate outcome				
	Raising Finance	**External Partnerships**	**Leading & Management**	**Cash Flow Mgmt.**	**Digital Tech.**
Support by programme					
Access to partners & customers		+++	+		++
Access to investors	++		+	++	
Access to peers	+++				
Testing & refining business model					
Help with team formation		+++	+++	+++	++
Direct funding from the programme	+++				
Business skills development		−		−−	−−
Press or media exposure					

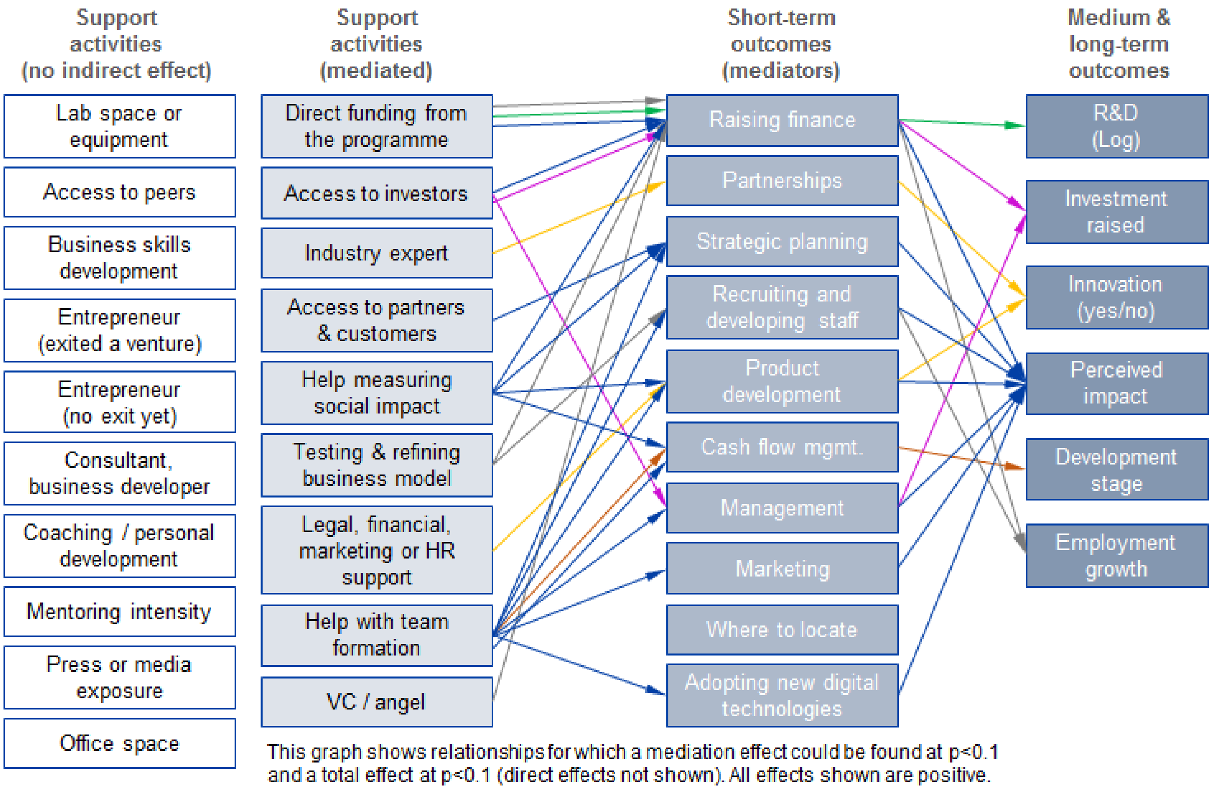
Lab space or equipment	++				
Legal, financial, marketing or HR support				+++	
Help measuring social impact	++			++	++
Office space					+
Coaching / personal development			+++	++	++
Mentoring support					
Industry expert					
Entrepreneur (exited a venture)			++		+
Entrepreneur (not exited)					
VC / angel	+++				
Consultant, business developer	−−	+++			
Mentoring intensity					

Table A29: Effect of intermediate outcomes on final outcomes. The table below shows the direction and significance of coefficients in optimised models for final outcomes (perceived impact of accelerators, employment growth, growth in employees with a degree, development stage, innovation, patenting, and R&D expenditures). For example, "+++" represents a coefficient that is positive and significant at the p<0.01 level. Similarly, "++" is a positive coefficient at the p<0.05 level, and "−" is a negative coefficient at the p<0.1 significance level. Intermediate outcomes are measured by respondents' answers to the question "Since applying to [programme name], to what extent have you changed your approach to:" on a five-point Likert scale from "Not at all" to "To a large extent", which we converted to numerical values for the purpose of OLS estimation. These models assume that all effects of accelerator and incubator support are mediated by intermediate outcomes (they include intermediate outcomes as explanatory variables but not variables measuring the support by programmes). Control variables are not shown. Results for growth of employees with a degree are all insignificant and have been omitted.

	Final outcome						
Intermediate outcome	**Perceived Impact**	**Employment growth**	**Development stage**	**Innovation**	**Patenting (Probit)**	**R&D (Probit)**	**Investment (Probit)**
Strategic planning	+++	−					
Product development							
Recruiting and developing staff		+++				++	
Marketing, attracting and keeping customers					+++		
Where to locate the enterprise							
Raising Finance	+++	+++	−	++		+++	+++

Partnerships with external organisations			+++	–
Leading and management	+	+		
Managing cash flow				–
Adopting new digital technologies (e.g. Customer Relationship Management (CRM), Marketing Automation or Project Management software)				

Figure A5: Pathways from support activities to startup success - accelerators only. This graph shows mediation relationships between startup support, changes in business practices and ultimate outcomes, based on the analysis in Figure 12 using the subsample of startups that participate in an accelerator. Sample size for analyses is between 166 to 192 accelerated startups, depending on data availability, per model.



This graph shows relationships for which a mediation effect could be found at p<0.1 and a total effect at p<0.1 (direct effects not shown). All effects shown are positive.

Appendix 5.13 Supplementary methods for ecosystem level analysis

To illustrate our approach, we begin by estimating the following "event-study" equation separately for early stage investments in high and low technology sectors:

Equation 1.

$$(1) \quad y_{bt} = \alpha_b + \sum_{i=-9}^{8} \beta_i D_i + \varepsilon_{bt}$$

where b indexes regions, t indexes time, ybt measures the number/value of early stage venture capital investments, and Di are indicator variables for the "event years" since the first accelerator launch in the local authority. The sample includes all the local authorities in Table A30 during the 2007-2018 period. For every local authority in the sample, we have information for 2 years before and 3 years after the first accelerator launch. The rest of the βs are estimated using variation of the regions with accelerator formation late (early) in the sample where information for a window of more than 2 years before (3 years after) the first launch is available.

We present the point estimates of equation (1) in Figure 13. Panel A (B) plots the estimates using the number (value) of early stage venture capital investments as dependent variable. In each plot, the solid line plots the estimates of the βs (relative to the year of the first accelerator launch, which is normalized to zero) l for the high-tech industry. The dotted line plots the estimates of the βs for the non-high-tech industry. Figure 13 shows indicative evidence of significant trend breaks in the number and value of early-stage venture capital investments in the high-tech sector following the first accelerator launch in the region (i.e., there is an increase in the slope of the solid line), that are not visible for early-stage venture capital investments in the non-high-tech sector (i.e., there is no change in slope of the dotted line). Moreover, the figure also shows no evidence of average differential pre-trends in the number or value of early stage venture capital investments between high and low technology industries (i.e., the solid and dotted lines have the same slope prior to the first accelerator launch).

We combine results from the separate event-study plots in Appendix 5.14, Table A32. We report results of the following model that tests whether a significant mean shift and/or a trend break exists in seed venture capital investments in the high-tech sector relative to the non-high-tech sector at the time of accelerator formation.

Equation 2.

$$(2) \quad y_{bit} = \alpha_{bi} + \gamma_{it} + \theta_{bt} + \delta Post \times High - Tech. + \beta\tau \times Post \times High - tech. + \varepsilon_{bit}$$

In equation (2), b indexes regions, i indexes sectors (i.e., high-tech and non-high-tech) and t indexes time. We include region cross sector (abi) and sector cross time (yt) fixed effects in the estimation to control for time-invariant heterogeneity between the high and low technology sectors in each region, and for differential time effects in high and low technology industries, respectively. We also include local authority cross time fixed effects (0bt), which allows us to compare changes in early stage venture capital activity between the high and low technology sectors for the same region, before and after the first accelerator launch. We cluster standard errors at the region cross time level.

The coefficients of interest are δ and β, which measure the average change in the mean and slope of the number/value of early-stage investments in the high-tech sector, relative to the non-high-tech sector, before and after the accelerator launch in a given local authority. These changes are relative to all regions that do not have their first accelerator launch in that year (but have either already had their accelerator launch, or will have a launch in the future), as is standard in event-time studies (see Bertrand and Mullanathain 2003)

Table A30: UK-based First Accelerator Programmes Founded 2008-2016. The table shows the names of the first accelerator programmes founded between 2008 and 2016 across different regions in UK excluding London.

Accelerator Name	Local Authority	Region	Year First Accelerator
Elevator Aberdeen	Aberdeen City Council	Aberdeen	2015
Propel Programme	Belfast City Council	Northern Ireland	2010
Entrepreneurs for the Future, Oxygen	Birmingham City Council	West Midlands	2011
First Bourne	Bournemouth Borough Council	South West	2016
Blue Lab	Brighton & Hove City Council	South East	2015
Qi3 Accelerator Bootcamp	Cambridge City Council	East of England	2012
Innovation Lab	Hart District Council_	South East	2016
Creative England Digital Accelerator	Hertsmere Borough Council	East of England	2014
Open Future North	Manchester City Council	North West	2016
Ignite Accelerator	Newcastle upon Tyne City Council	North East	2012
Capital One Growth Labs	Nottingham City Council	East Midlands	2016
Beta Foundry	Oxford City Council	South East	2011

Drive with Belron	Runnymede Borough Council	South East	2016
UP Accelerator	Salford City Council	North West	2014
Dotforge	Sheffield City Council	Yorkshire and Humberside	2013
Ideas Fund	Swansea City and Borough Council	Wales	2016
ESA Business Incubation Centre Harwell	Vale of White Horse District Council	South East	2011

Table A31: Summary Statistics: The table shows summary statistics of the main variables used in the analysis.

	Observations	Mean	Std. Dev.	Min	Max

Number	406	4.45	6.62	0	47
Number non Accelerated	406	3.42	5.01	0	39
Amount	406	2,790,203	10,300,000	0	121,000,000
Amount non accelerated	406	2,496,098	9,601,757	0	116,000,000
Log Amount	406	14.79	0.73	14.29	18.62
Log amount non accelerated	406	14.63	0.75	14.13	18.58
Post	406	0.43	0.5	0	1
High-tech	406	0.5	0.5	0	1
Post× High-tech	406	0.22	0.41	0	1
Trend	406	1.08	1.83	0	7
Post× High-tech	406	0.54	1.4	0	7

Appendix 5.14 Supplementary results for ecosystem level analysis

Our results from estimating equation (2) confirm that the patterns in Figure 13 are statistically significant: there is a robust trend break in early-stage venture capital investments in the high-tech industry (relative to the non-high-tech industry) after the first accelerator launch in a given local authority (i.e., the coefficient of t×Post×High-tech is positive and statistically significant).

The interpretation of the coefficient of t×Post×High-tech in column 1 is that the number early-stage venture capital investments in the high-tech sector increases by 1.745 for every year after the first accelerator launch (i.e., the first year there are 1.745 additional investments, in the second year there are 3.49=1.745*2 additional investments etc.), which corresponds to 40% of the unconditional number of investments (4.45; see Table A31). This estimate is economically significant: within 5 years of accelerator formation, 26 additional investments in the high-tech industry are estimated to take place in a given region, relative to the non-high-tech industry.

The coefficient in Column 2 of Table A32 shows that the slope increase in the number of investments following the accelerator launch is not driven by the companies that participate in the accelerator programmes—the estimated trend break continues to be statistically and economically significant, once we exclude accelerated companies from the count.

Columns 3-6 show that the trend break in the number of investments, is also significant in the value of the early stage venture capital investments. The interpretation of the coefficient of t×Post×High-tech in column 3 is that the value of early-stage venture capital investments in the high-tech industry increases by £3.2 million for every year after the first accelerator launch, which corresponds to 114% of the unconditional value of investments (£2.79 million; see Table A31). This estimate is economically significant: within 5 years of accelerator formation, an additional £48 million are invested in the high-tech industry, relative to the non-high-tech industry. The estimate is not driven by companies that participate in accelerators: column 4 shows a similar estimate after we exclude accelerated companies from the sample. It is also not driven by outliers: columns 4-6 show evidence of the same trend break using a logarithmic transformation of the value of investments. Columns 3 and 4 show an apparent negative mean shift after accelerator formation. However, columns 5 and 6 show that this effect is driven by outliers, as is no longer significant once we run the specification in logs.

Table A32: Accelerator Formation and Early-Stage Venture Capital Investment in the High-tech industry. The table presents results from estimating equation (2). The standard errors are presented in parentheses and are adjusted for heteroscedasticity and clustered at the borough cross year level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Number	**Number non accelerated**	**Amount (£ M)**	**Amount non accelerated (£ M)**	**Log amount**	**Log amount non accelerated**
Post×High-tech.	1.243	0.841	-4.892**	-4.607**	-0.173	-0.163
	(1.006)	(0.904)	(2.296)	(2.180)	(0.145)	(0.157)
Trend×High-tech	1.745***	1.160***	3.236***	2.820,***	0.117***	0.098**
	(0.350)	(0.313)	(1.033)	(0.991)	(0.044)	(0.048)
Observations	406	406	406	406	406	406
R-squared	0.912	0.889	0.781	0.774	0.878	0.863

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